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Improving Patient Access: Using Computer Simulation to Increase the Operational Efficiency of an Academic Sleep Centre

by

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Abstract

Objectives: Access to timely therapy is problematic for patients with sleep disorders. The purpose of the current study was to identify and mitigate operational barriers to access for patients referred to an academic sleep centre (SC).

Methods: A discrete-event simulation (DES) model of patient flow was used to identify sources of congestion. Alternative model configurations were tested for effects on time from referral to treatment initiation. Results were analyzed by urgency and diagnosis.

Results: Simulation results revealed that removal of triage urgency and increased physician capacity improved access. The elimination of alternate care provider clinics dramatically worsened outcomes. Increasing respiratory therapist capacity did not affect model outcomes, but improved utilization. Physician supply and resources for advanced diagnostic testing were deemed insufficient to meet referral demand.

Conclusion: The DES model quantified impacts of operational policies that could improve access to the SC, although inadequate supply was also identified as a contributor to long waiting lists.

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Dedication

This thesis is dedicated to my family. Aai and Baba, you have provided me with immeasurable love and support in all of my aspirations, career and otherwise. Sonu, your constant encouragement has been wonderful and comforting.

To Maya, whose smiling face and enthusiastic "Baba" interrupted my work so often. But it was worth it.

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List of Abbreviations

Symbol	Definition
AHS	Alberta Health Services
CI	confidence interval
CIS	Clinic Information System
CPAP	continuous positive airway pressure (alternate care provider clinic)
CRN	common random numbers
CTS	Canadian Thoracic Society
DES	discrete-event simulation
FTE	full-time equivalent
OQN	open queueing network
OR	operations research
OSA	obstructive sleep apnea
PAP	positive airway pressure
PSG	polysomnography (in-laboratory sleep test)

RT	respiratory therapist
SC	Foothills Sleep Centre
SD	standard deviation
SDB	sleep-disordered breathing
SEP	sleep expert panel
SSAT	Snoresat (ambulatory sleep test)
$T_{Initial}$	time to initial physician visit
T_{PSG}	time to initial polysomnogram
T_{Treat}	time to initiation of treatment
V&V	verification and validation

Chapter 1: Introduction

An aging population and advancements in medical diagnosis and therapy have dramatically increased the demands on a limited pool of healthcare resources. Consequently, patients experience delays in accessing health services, often independent of disease severity, disease progression or quality of life (1). While it is often assumed that imbalances between health system capacity and patient demand promote the expansion of waiting lists, studies from the field of operations research (OR) have shown that waiting time reductions can often be achieved by making more effective use of available capacity (2,3).

Sleep disorders are highly prevalent in the general population, and have significant effects on health and healthcare utilization (4-12). The challenges in providing timely access to diagnostic sleep testing and sleep subspecialist care are widespread (13). These difficulties have sparked an interest in novel modes of healthcare delivery, such as ambulatory sleep testing and nurse-led management of sleep disorders (14-16). However, the studies of alternate care pathways have emphasized clinical outcomes only and have not examined how these delivery models might affect patient flow or access to health services.

The Foothills Sleep Centre (SC) is the major provider of sleep diagnostics and medical care of sleep disorders in Southern Alberta. Despite providing over 5000 multidisciplinary visits annually, the SC currently has a waiting time of over one year from referral to assessment. Additionally, once a patient has been assessed, further

delays for advanced diagnostic testing are common. These delays are a major concern for SC administrators. Thus, the objectives of this study were:

- To explore the operational barriers to access at the SC
- To identify operational policies that could mitigate these barriers

Given the complexity of care pathways at the SC, simulation modeling was chosen as the preferred approach for the current study. Discrete-event simulation (DES) is a modeling approach that is particularly suited to the analysis of queues and system congestion. A DES model was constructed and used to describe the flow of patients through the SC. Based on the resource constraints identified from the model, a number of novel operational policies were proposed. These alternative configurations were tested in the model to determine their effects on access to diagnosis and treatment.

This thesis begins with a description of sleep disorders and related models of care, to highlight the importance of timely access to treatment for these conditions. A discussion of the use of OR in healthcare follows, including a review of queueing theory, DES and the implications for sleep disorders. With this context established, the study methodology is described, including details about the process description, model conceptualization and construction, and data analysis. Subsequently, the presentation of the study results highlights findings from the preliminary analysis of historical SC data and from the analysis of model outputs. Finally, a discussion of these results is provided, including the implications of the study outcomes and insights about the SC from the input data analysis and model performance. Limitations of the current study, the

considerations for study replication at another sleep centre, and potential areas for future OR research at the SC are also described.

Chapter 2: Sleep Disorders and Models of Care

Sleep disorders are common. Population prevalence estimates for symptomatic sleep disorders are as high as 10% (4-12,17). Furthermore, sleep disturbances are associated with an increased risk of work-related disability and negatively affect the likelihood of returning to work after injury (18). Multiple sleep disorders may coexist in a given patient. The clinical implications of simultaneous sleep disorders have not been clearly delineated.

This chapter describes the epidemiology, diagnosis and clinical implications of sleep disorders and highlights the importance of timely access to diagnosis and treatment. An exploration of health service delivery for sleep disorders follows. This discussion provides a general overview of models of sleep care in Canada, but focuses on the delivery of sleep services in Calgary.

Respiratory Sleep Disorders

Sleep-disordered breathing (SDB) represents a spectrum of disorders that includes obstructive sleep apnea (OSA), central sleep apnea (CSA) and hypoventilation. OSA, the most common of these, affects up to 24% of men and 9% of women (19). Untreated severe OSA has been associated with an increased risk of cardiovascular disease, including hypertension, stroke, and both fatal and nonfatal cardiovascular events (7-9,12). Additionally, patients with OSA are at increased risk for motor vehicle crashes (6), use more healthcare resources (20), and may experience reduced survival compared to those

without OSA (21). Treatment of OSA reduces the risk of both cardiovascular events and motor vehicle crashes (7,22,23).

CSA occurs in association with a number of medical conditions, including neurologic disease, narcotic use and congestive heart failure. The population prevalence is unknown, but in heart failure patients, CSA occurs in 33% (24) and portends a poor prognosis (25). The clinical significance of CSA in patients without heart failure is unclear.

Hypoventilation may occur in obese patients, some patients with severe longstanding OSA, and in association with other respiratory diseases. Although a heterogeneous group, these patients are at higher risk overall for respiratory failure, hospital admission and death than the general population (26).

The diagnosis of SDB is based on clinical assessment and sleep diagnostic testing. The current gold standard test for the diagnosis of SDB is a polysomnogram (PSG), during which the patient sleeps in the laboratory while connected to a number of sleep monitors. In some sleep centres, OSA is diagnosed using an ambulatory sleep monitor while the patient sleeps at home. This diagnostic tool has been shown to accurately diagnose OSA (14) and is increasingly used in diagnostic pathways for OSA (15). Clinical assessment and treatment of OSA is generally performed by trained sleep physicians. Recent studies have demonstrated that nurse-led care (27), or treatment by family physicians (28), may result in similar outcomes to specialist-led care for patients with uncomplicated OSA.

The treatment of SDB often involves lifestyle measures, positive airway pressure therapy (PAP), or a dental appliance, and may involve oxygen in those with hypoventilation. Follow-up care may be provided by a physician but may also be provided by respiratory therapists (see *Service Delivery for Sleep Disorders* below). The frequency of follow-up visits depends on individual practice patterns and the severity of SDB.

Non-Respiratory Sleep Disorders

A number of non-respiratory conditions can adversely affect sleep. Examples include insomnia, restless legs syndrome, periodic limb movement disorder, narcolepsy, shift work sleep disorder, mood disorders, medication-related sleep disturbances and chronic sleep deprivation due to lifestyle or occupational factors. The prevalence of these disorders is variable but ranges from 0.5-10% (4,17,29). Quality of life is reduced in patients with non-respiratory sleep disorders (4,5,17). Moreover, there may be an association between restless legs syndrome and cardiovascular disease (30). Finally, short or long sleep duration is a predictor of death (31).

The diagnosis of non-respiratory sleep disorders is based on clinical assessment, with PSG providing added diagnostic information for some disorders. Insomnia, shift-work disorder, restless legs syndrome and mood or medication-related sleep disturbances can typically be diagnosed with clinical history and sleep diaries, although PSG may occasionally be used if there is diagnostic uncertainty. Conditions such as narcolepsy and periodic limb movement disorder typically require polysomnography and related testing

for diagnosis (32). The ambulatory sleep test used to diagnose OSA is unhelpful for non-respiratory disorders.

Many family physicians diagnose and treat non-respiratory sleep disorders, such as insomnia, mood or medication-related disorders and restless legs syndrome. Assessment by a sleep specialist may be indicated for the treatment of these disorders in refractory cases, and for the diagnosis and treatment of other disorders. Alternate care providers such as psychologists are used for specific subsets of patients with insomnia *(see Service Delivery for Sleep Disorders* below). Treatments typically involve pharmacologic, lifestyle and psychotherapeutic measures, depending on the diagnosis. Follow-up may be quite extensive depending on practice patterns and disease severity. There is no literature on optimal care pathways for patients with non-respiratory sleep disorders.

Service Delivery for Sleep Disorders

Models of care for sleep disorders vary greatly. These range from independent practitioners, using local diagnostic testing facilities, to integrated sleep centres within which practitioner clinics and diagnostic testing both occur. Similarly, new patient referrals for assessment of sleep disorders may be directed to individual physicians or referral pools. Finally, in some settings, patients may be referred to a sleep centre for testing only.

There is also considerable variability in the definition of a sleep practitioner. The traditional model for sleep care entails physician-based assessment and follow-up care.

While uncomplicated sleep disorders may be managed by non-sleep experts, the requirement for sleep specialty training and certification is increasingly being mandated for both the interpretation of sleep studies and the care of patients with complex sleep disorders (33). Beyond the physician-centred model, alternate care providers are increasingly used in some centres. These respiratory therapists, nurses and psychologists can provide specialized care to patients, usually with physician support as needed for more complex issues (27). Alternate care providers may be used for primary assessment or for follow-up care after patients are seen by a physician.

Overnight PSG is the gold standard for sleep diagnostics. This test requires a patient to sleep in a laboratory bed while monitored by a PSG technologist. The PSG technologist reviews the test data and scores sleep stages and both respiratory and non-respiratory abnormalities during sleep. A clinical interpretation is subsequently provided by a sleep physician. Due to advancements in technology and limitations in access to PSG, ambulatory monitoring has emerged as a diagnostic tool for SDB (13,16). Although significantly less information on sleep quality and non-respiratory abnormalities is available from this test, the volume of referred patients with SDB makes this a useful adjunct to PSG (34). Ambulatory testing is cheaper and is not constrained by bed or technologist availability, thus providing the potential for improved access to diagnostic testing for patients with SDB.

The funding for sleep services in Canada varies across the Provinces. Physicians are paid through public healthcare budgets for patient care services. Diagnostic testing is also

publicly funded, although with different financial models. In most Provinces, the operation of sleep laboratories is funded through hospital budgets. In contrast, the Ontario government pays for both the technical aspects of sleep laboratory operation and professional reimbursement for test interpretation, on a fee-for-service basis (13). Costs for pharmacologic and PAP therapy are borne by patients or through private insurance, with varying degrees of cost reimbursement from provincial health plans. Private homecare companies also provide ambulatory diagnostic testing in Provinces where access to publicly funded services is limited. Finally, some private sleep clinics offer PSG testing with direct charges to the patient, often in conjunction with assessment by a physician.

Foothills Sleep Centre

The focus of the current study is the Foothills Sleep Centre (SC), which is a publicly funded academic sleep centre in Calgary, Alberta. The SC is one of two centres that provide publicly funded diagnostic testing and clinical services for Southern Alberta. Additionally, the SC is the only tertiary referral sleep centre for Southern Alberta and Eastern British Columbia, providing these services for some two million people. Approximately 2500 referrals are received annually, and over 5000 patient visits occur each year. Diagnostic services include over 1000 PSG tests and almost 2000 ambulatory tests (SSAT) (35).

Diagnostic testing at the SC includes four beds for PSG testing, and 10 ambulatory monitors. Testing is offered 5 nights per week, resulting in a weekly capacity of 20 PSG

and 50 SSAT tests. Clinical services are provided by six respiratory physicians, one neurologist, two general internists and one general practitioner. Each physician holds one or two clinics per week, which do not occur when the physician has on-call responsibilities or vacation scheduled. Alternate care providers include a psychologist with expertise in insomnia care and respiratory therapists. The psychologist accepts newly referred patients and referrals from other practitioners at the SC. The respiratory therapists assess patients with SDB who are prescribed PAP therapy. Patients arrive for respiratory therapist assessment from new referrals or from other practitioners.

Referrals for assessment of sleep disorders are processed through a central intake and triage system. Triage of new referrals is used to prioritize patients as urgent, semi-urgent or normal urgency based on the severity of daytime sleepiness, comorbidities, previous sleep testing and occupation. Since only some physicians have undergone sleep specialty training or certification, the allocation of patients to a particular physician is based on the suspected diagnosis and the physician's expertise. Additionally, some non-sleep physicians in Calgary are able to order SSAT testing, without a referral for assessment. PSG is only available to sleep specialists, although they may order and interpret PSG tests for certain non-sleep specialists without a referral. PSG tests are also prioritized as high or normal urgency at the discretion of the ordering physician.

Patients arriving to the SC may take a number of paths. Figure 1 provides an overview of the important clinical pathways and the percentage of patients flowing between processes at the SC. Patients who are classified as "Primary Urgent" based on the referral

information (approximately 10%) are scheduled for physician assessment with highest priority and do not undergo any testing in advance of this appointment. All remaining referred patients are sent a questionnaire that is used to determine triage priority through a "Secondary Triage" process. All patients processed through the "Secondary Triage" process who have not had SSAT testing prior to referral (approximately 30%) undergo SSAT testing before the initial clinician visit occurs. Of note, patients who enter the system for diagnostic testing only do not undergo triage prioritization and usually leave the system after the requested sleep test is completed.

Any patients who are referred with sleep problems that can clearly be assessed and treated by the psychologist or respiratory therapists will be scheduled to see these providers. All other patients are scheduled with a sleep physician. Patients who are deemed to require a physician assessment are assigned to the most appropriate physician based on the suspected diagnosis. For some diagnoses, more than one physician is acceptable; for these situations, the patient is assigned to the next available of these physicians. For example, patients with uncomplicated OSA can be assessed by any of the respirologists, neurologist, general internist or physicians who only see OSA, and will be assigned to the physician with the earliest available appointment. In contrast, patients with complex respiratory disease can only be assigned to a respirologist. Patients will typically have all their physician visits with the physician to whom they were initially assigned, unless this physician seeks the advice of another physician with specific expertise. These internal referrals to other physicians are uncommon.

After the initial clinician assessment, patient trajectories vary significantly. Depending on the presenting complaint and medical history, patients may undergo further diagnostic testing (PSG or repeat SSAT). Many patients who were initially seen by a physician are referred to the CPAP clinic or psychologist. Patients may also be scheduled for a follow-up clinical visit after other diagnostic testing is completed. Finally, some patients are discharged from the clinic, as they are determined to have a problem that is unrelated to their sleep or have a milder complaint that is addressed at the first visit.

Subsequent visits include further testing or clinician visits as is deemed necessary by the clinical provider and patient. These visits are usually for discussion of a sleep test result, follow-up of the patient's response to treatment for a sleep disorder, or to explore new sleep problems or treatment difficulties experienced by the patient. Depending on the diagnosis, patients whose sleep problems have resolved with treatment are either discharged from the clinic or followed indefinitely.

Access to Diagnosis and Treatment of Sleep Disorders

Given the large catchment area, high prevalence of sleep disorders and limited resources for testing and clinical care, access to the SC for patients with sleep disorders is problematic (13). Currently, the waiting time for non-urgent initial assessment at the SC exceeds one year from the time of referral. Once an initial assessment is completed, the waiting time for non-urgent PSG is approximately six months. As a result, the time from referral to treatment of a sleep disorder may approach two years for many patients.

Given the significant clinical consequences of untreated sleep disorders, this delay has been identified as a major health services problem (13).

The problem of delays for sleep care is not unique to Calgary. Waiting times for sleep specialist assessment range from three to 36 months in Alberta (36). Furthermore, a survey of Ontario physicians caring for patients with OSA revealed delays of 11 to 16 months to initiate treatment (37). Finally, limited access to both diagnostic testing and specialist assessment for sleep disorders has been reported in the United States, Europe and Australia (13,38). The prevailing notion is that inadequate resource capacity is the primary cause of these long waiting times, but no study has examined the contribution of operational inefficiencies. More research is needed to more clearly define the factors that lead to these delays, with the ultimate goal of improving access to sleep services internationally.

Chapter 3: Operations Research and Simulation in Healthcare

Operations research (OR) can be defined as a "science that helps to improve operations in various organizations" using optimization methods, planning under uncertainty and efficiently solving complex, large-scale problems (39). Though first applied to healthcare in 1952 (40), operations research has not been widely accepted. Recent challenges with resource constraints and increased demands for timely medical care have heralded the emergence of OR techniques in health system analysis and redesign. Facets of OR that have been applied to healthcare include appointment scheduling (41), resource allocation (42), queuing theory (43) and simulation (44).

This chapter highlights the use of OR for important healthcare problems. Modeling techniques are emphasized, with a particular focus on simulation as a means of analyzing complex systems. Discrete-event simulation (DES) is presented as the ideal simulation methodology for the current study, with a description of the theoretical underpinnings of DES. Finally, the dearth of OR studies examining the problem of access to sleep services is presented as a rationale for the current study.

Operations Research in Healthcare

OR techniques have been applied to many different types of healthcare problems, including scheduling, resource allocation, facility planning and medical decision-making. Appointment scheduling problems typically involve the determination of the best scheduling policy given the capacity and demand variation created by a number of

patient, provider and system characteristics (45). Patient characteristics that have been explored include clinical urgency (46,47), the time required to serve the patient (46-50), and cancellations or missed appointments (51-56). In the OR literature, studies of physician factors have typically been limited to tardiness for a scheduled clinic (51,57-59). Examples of system characteristics that have been examined in the OR literature include queueing policies (41,60), the number of patients scheduled in a given clinic (61) and the allowance for unscheduled ('walk-in') visits (62,63). Although many of these studies have been focused on individual clinics, the findings have provided insights into the considerations required to optimize scheduling policies more broadly.

Resource allocation and facility planning studies seek to ensure that appropriate services are being delivered efficiently and comprehensively in a system of interest. In a single clinic, optimizing resources has involved matching physician supply with referral demand to reduce delays in accessing care for medical disorders (64). Additionally, clinic space and operating rooms, which are often under high demand by physicians, have been allocated in a systematic way using optimization methodology and simulation (59,65-67). On a larger scale, efficient system redesign of municipal laboratory facilities has been accomplished using resource pooling and simulation (68).

More recently, OR methods have been applied to clinical problems. Mathematical optimization was used to maximize the radiation dose to lung tumours while minimizing the exposure to healthy tissue in the face of motion uncertainty due to breathing (69). Furthermore, a simulation of multiple allocation strategies for liver transplantation was

used to determine the policy that would maximize survival for transplant recipients (44). While such examples exist and have shown their value, operations research has not been widely accepted in healthcare. Moreover, a great deal of the published research deals with context-specific, local problems, without generalizability of the results.

Analytical Modeling

Mathematical modeling is a fundamental tool in OR. The choice of modeling technique depends on the question of interest, features of the system being modeled and the availability of time and other resources (70). Analytical models provide exact solutions, given a set of input values (71). Optimization is an analytical method that has been used for healthcare problems. Two types of optimization methods are linear and nonlinear programming, in which the aim is to optimize an outcome variable by changing decision variables in the context of known constraints. Linear programming has been used to allocate operating room resources to surgical specialties in hospitals (42,66). Underlying these optimization problems was the goal of providing adequate operating time to each surgical specialty, using utilization and demand data, under the constraints of operating room and staff availability. This approach is useful when optimal decisions can be derived from deterministic input parameters. However, optimization models require simplifying assumptions to arrive at constant input values. These assumptions may represent an oversimplification of the system under study, thus limiting the utility of such models for the analysis of more complex systems.

As described above, the complex nature of many systems often precludes a deterministic approach to problems. Sensitivity analyses can be used to explore the effects of changing input parameters on model performance (72). However, the solution of optimization problems is ultimately driven by constant input values.

Stochastic models are analytical models that incorporate uncertainty into model inputs. They are used in systems in which variability is a critical element of the problem under study (70). Markov modeling is one stochastic modeling approach that is commonly used for healthcare problems. These models are used to describe systems based on transitional probabilities from one state to another. Fundamental to Markov models are the assumptions that the transitional probabilities depend on the current state only and are independent of the past. Such models are effective for analyses in which the population under study is assumed to be homogeneous, as in the assessment of care patterns of patients discharged after an acute stroke (73), or in a pharmacoeconomic evaluation of vaccination strategies for influenza (74). Markov models aid decision-making by describing the distribution of the study population across each state, although the assumption of homogeneity of the study population limits their utility for more diverse populations. Furthermore, Markov models are inadequate for highly variable medical systems (70).

Discrete-Event Simulation

Simulation is increasingly used to model the behaviour of complex medical systems, particularly when the system cannot be represented accurately by simpler mathematical

models. Static simulation models, such as Monte Carlo simulation, represent systems for which the problem is independent of time. In contrast, dynamic models are used for problems for which time is an important factor (71).

DES is a type of simulation that models the evolution of a system over time. The model is composed of state variables that change instantaneously at discrete time points (71). DES can be used to describe the performance of healthcare systems. Moreover, DES may be used to compare alternative system designs before implementing actual system changes. It is best suited to problems in which the desired performance measures are related to resource utilization, queue length and patient flow (70).

DES has many advantages for modeling operational aspects of healthcare systems. Like other simulation techniques, DES provides an experimental environment in which alternative scenarios can be tested under a variety of experimental conditions. Such experiments can be conducted over long simulated time periods without requiring changes to the system under study (71). DES is particularly useful for healthcare systems, which are characterized by complex interactions of patients, providers and physical resources, such as beds or diagnostic technologies. Additionally, there is significant variability in patient characteristics and provider behaviour, limiting the utility of simpler stochastic models. This variability can be exploited in DES models, making this technique a powerful tool for understanding healthcare systems (75).

Irrespective of this value, there may be disadvantages to DES that could limit its use in healthcare. Since each simulation output is an estimate based on probability

distributions, multiple replications are required to increase the statistical confidence in model outputs. Due to this need for multiple replications and the system complexity that is represented in DES models, the modeling process is time-consuming (71). As well, and historically, simulation has not been accepted by healthcare professionals and administrators, due to a poor understanding of its benefits and negative attitudes toward conceptualizing clinical care as a process design or workflow problem (76).

Queueing Theory and DES

In healthcare systems, queues for healthcare services translate into delays to receive assessment and treatment for medical disorders. The components of a queueing system are an arrival process, service mechanism and queue discipline. Arrivals are random and are described by a mean arrival rate (λ), which is the number of patients arriving per unit time. The service mechanism is comprised of both the number of available servers (s) and random service times with a mean service rate (μ). Finally, the queue discipline describes the priority sequence by which arriving patients are placed in the queue for service (71).

Queueing systems are described using the above variables. Common performance measures for queueing systems include averages of queue length, time in queue, number in system and time in system. The calculation of these performance measures depends on the probability distributions used to describe the random variables in the queueing model. Another important performance measure of a queueing system is the utilization of servers

(ρ), which is defined as the mean arrival rate divided by the product of the number of servers and the mean service rate ($\rho = \lambda/s\mu$).

Importantly, analysis using these performance measures is only possible for a steady-state system. Steady-state occurs when sequential observations of a particular performance measure have approximately the same distribution (71). Thus, over multiple replications, the mean value of that performance measure is similar over time. Utilization values that are greater than one suggest that a system is not in steady-state.

A framework for approaching improvements to a queueing system is through the application of Little's Law, which states that the mean number of patients in the system (L) is equal to the product of the mean arrival rate (λ) and the mean time in system (W) ($L = \lambda W$) (77). Thus, the congestion of a steady-state system can be improved by reducing either the mean arrival rate or the mean time spent in system, independent of the underlying probability distributions. Little's Law can be applied to the entire system under study or target a specific aspect of the system (e.g. a queue or a specific patient population).

It can be mathematically shown that as utilization increases, system congestion also increases (71). Thus, Little's Law suggests that for a given mean arrival rate, system congestion can be improved by lowering server utilization. Utilization can be improved by increasing server capacity or by changing service delivery such that the mean service time is reduced. Furthermore, increased variability in service time or arrivals also contributes to queue formation (3). For example, triage systems that reserve resources

for use by higher priority patients may paradoxically worsen delays due to increased demand variation (3). Thus, effective queueing policies may reduce variability and improve congestion. Similarly, using a single queue in multiple server systems may reduce both the mean time in the system and the variance of waiting times (2).

DES is well suited to queueing systems in that it emphasizes queue length, system delays and processing times. The principles of queueing theory described above generally apply to single systems. In contrast, many healthcare systems consist of a network of queues, each with different service and arrival characteristics. DES models can demonstrate the effects of changes to one queueing system on other aspects of the larger system. Furthermore, the experimental environment of a DES model facilitates study of the combined effects of system improvements. Finally, whereas some of the queueing concepts discussed above are only valid in steady-state, DES models provide a broader scope for analyzing non-stationary problems.

DES in Healthcare

Appointment scheduling has been a prime focus of DES in healthcare. Vasilakis *et al.* studied the effects of a single-queue, multi-server referral model on access to surgical assessment (41). Using a pooled appointment scheduling system rather than scheduling by individual surgeon, this group demonstrated a reduction in waiting time from referral to assessment. Klassen and Rohleder showed that by scheduling patients whose expected appointment duration was likely to have the least variation at the beginning of a clinic, the amount of time spent waiting by patients and physicians could be reduced (46). The

same authors found that simulation of clinic scheduling for single-day and multi-day appointment booking systems resulted in similar scheduling rules to minimize patient waiting times and physician idle time (47).

Resource allocation is another pillar of operations research that has relevance to healthcare systems. In their DES analysis of the British Columbia Cancer Agency Ambulatory Care Unit, Santibáñez and colleagues showed that flexible allocation of rooms to different oncologic specialty clinics, rather than a 'pod-based' allocation system, could result in a 25% decrease in room requirements for a given patient volume as well as a 70% reduction in waiting times(59). Rohleder and colleagues demonstrated that compared to the current system of 25 clinical laboratory service centres in the Calgary Health Region, redistributing the available resources across 12 service centres would reduce mean waiting times by approximately 50 minutes, including a 98% reduction in the number of patrons experiencing prolonged waits (68). These performance improvements were attributed to the greater matching of pooled resource capacity and patient demand. DES was also used to promote a novel method for analyzing cervical cancer screening samples, with the expected turnaround time for reporting results decreasing from 11 weeks to 2 weeks (78).

Much of the previous work using DES has focused on single clinics with fairly uniform patient populations. Elkhuizen and colleagues sought to generalize the modeling process by applying a DES model produced for a neurology clinic to gynecology and preoperative clinics in the same hospital (64,79). However, Elkhuizen merely applied the

same model to another uniform patient population, rather than simultaneously addressing a variety of patient types. Additionally, the only performance measure studied was access for new patient consultations, without consideration of follow-up assessments or other operational aspects of the clinics. In contrast, Santibáñez and colleagues built an outpatient DES model that incorporated various oncologic specialties with different resource requirements and appointment lengths (59). While the literature abounds with papers making important contributions to the understanding of healthcare operations management, there are no published studies of outpatient care that incorporate diagnostic testing and clinical care pathways. An example of a system requiring integrated services is the care of patients with sleep disorders, for which there is a dearth of operations research.

Operations Research and Sleep Medicine

Current challenges in the field of sleep medicine include long waiting times for diagnostic testing and specialist assessment (13,38). Ambulatory testing has been emphasized over conventional laboratory-based diagnosis as a means of improving access to the diagnosis of one common disorder, obstructive sleep apnea (OSA) (15,16). For uncomplicated OSA, clinical care by specialist nurses has been shown to achieve similar clinical outcomes as specialist physician assessment (27), with a possible reduction in cost. Markov models have been used to streamline decision-making regarding the diagnosis, therapy and prognostication of OSA, with a suggestion of improved clinical outcomes (80).

The literature examining alternative pathways for sleep care has thus far emphasized clinical rather than operational performance measures, and has focused on OSA rather than the full spectrum of sleep disorders seen at most sleep centres. While extensive research is lacking in the areas of efficiency and reduction of variation in sleep care, there has been some recent interest in applying OR concepts to clinical sleep centres. For example, operational analysis was used to facilitate the amalgamation of two sleep centres in Manitoba (81). This system redesign resulted in access improvements for Manitobans with sleep disorders. However, this project involved the simultaneous implementation of multiple system changes, making it difficult for the effects of any one improvement strategy to be ascertained. Thus, while new efforts are being made to understand the operational aspects of sleep medicine, there is still a lack of generalizable research in this area.

Further studies of service delivery models at sleep centres will not only help improve access to quality sleep care but may highlight themes that could be applied and generalized to other sleep centres as well.

Chapter 4: Methods

Study Design

The present study involved the design and implementation of a discrete-event simulation (DES) model of the Foothills Sleep Centre (SC). The SC is a multidisciplinary sleep clinic providing diagnostic and clinical sleep services for patients with a range of sleep disorders (see Service Delivery for Sleep Disorders in Chapter 2). Patient flow at the SC involves interactions between patients, clinicians and diagnostic testing resources through a complex network of queues and clinical pathways. Furthermore, appointment scheduling based on clinical patient characteristics and clinician or test resource availability features prominently. The methodology underlying the construction and use of the DES model is outlined in subsequent sections.

Process Description

To define a data structure and conceptualize the model, a detailed understanding of the system under study is required. A process description was created after consultation with care providers, managers and clerical staff at the SC. The process description also incorporated historical data from existing clinical and administrative databases. For each process at the SC, the process description details patient arrival patterns and relevant clinical characteristics, resource availability and requirements, workflow, and queueing and scheduling policies. The process description was used to identify input data deficiencies for which simplifying approximations would be required, and informed

database modifications for future data collection. The process description was summarized in two documents, which are found in Appendices A and B. The first, entitled "Process Description of Foothills Sleep Centre" (Appendix A), details workflow, scheduling rules and resource requirements at each process within the sleep centre. The second, entitled "Data Description for Foothills Sleep Centre DES Model" (Appendix B), describes the input data sources for the DES model. Further details of data collection are provided in *Data Collection and Input Data*, below. Additionally, an overview of the flow of patients through the SC is provided in Figure 1, with a summary of clinical pathways presented in Chapter 2 (See *Foothills Sleep Centre* in Chapter 2).

Data Collection and Input Data

Clinical data for each process at the SC is collected using Microsoft Access (Microsoft Corporation, Redmond WA) and Structured Query Language databases. Additionally, a clinic information system (CIS) is used for scheduling appointments and for tracking of provider availability, patient visits, and cancelled or missed appointments. These databases were linked through Microsoft Access using the patient's system identification number to allow for queries with data in both databases (e.g. the urgency of a test linked to the test date). While visit dates were available within CIS, the clinical database was modified to add time stamps for other important processing steps in a patient's trajectory, including:

- Date that referral was received
- Date that triage urgency and provider were assigned

- Requisition date for in-laboratory and ambulatory sleep study

In addition, the following clinical information relevant to triage decisions and flow pathways was added:

- Urgency category with reasons for urgency rating
- Epworth Sleepiness Score
- Indicator of high-risk occupation
- Likely diagnosis
- Provider type (based on likely diagnosis) and provider assignment
- Indicator that patient was re-referred
- Visit type for alternate care provider clinic
- Requisition urgency for in-laboratory or ambulatory sleep study
- Details of reasons for discharge (e.g. failure to return questionnaire, too many cancellations, etc.)

If data available after the database modification was adequate in quality and quantity for use as input data in the DES model, it was used in place of data approximations (e.g. the proportion of provider visits that were conducted by telephone). The database modifications were maintained to improve the input data for future simulation projects.

Queries from the databases described above were used to derive two types of input data. Both of these data types are described in Appendix B, entitled “Data Description for Foothills Sleep Centre DES Model”. Information on physician availability for clinics was derived from CIS data from January 2008 to December 2010. The probabilities of

cancelled or missed appointments were calculated using CIS data from January 2008 to August 2010. These timeframes for data collection were determined to be appropriate as they were recent but also far enough in the past to accurately represent these variables over time.

The second type of input data was patient data. In a DES model of a healthcare system, empirical or probabilistic inputs can be used to assign patient factors that will determine queueing policies or flow pathways. However, there is likely a significant correlation between patient characteristics and decisions regarding the number, frequency and priority of clinical visits. Thus, actual visit history from a representative sample of 150 actual patients was used for patient input data (see *Data Analysis* below for sample size calculation). Given the long delays from referral to diagnosis and treatment, and in order to capture as much of the patient's visit history as possible, the sample was taken from patients referred to the SC in 2007. The patient sample was taken from referred patients with at least one visit for testing or clinical assessment, since those patients without visits were those who dropped out of the referral process before their first visit. The visit history included all visits that occurred by December 31, 2010. All input data for a given patient was compiled in a single record for that patient.

Due to data deficiencies in the clinical databases, certain clinical information that was relevant to flow pathways and queueing policies was lacking. Thus, a review of patient charts was performed for all patients in the dataset. Clinical data obtained from this chart review included information from screening questionnaires and test data as well as

urgency ratings and provider assignments that occur as part of the referral and triage process. The chart review and data entry into each patient's record was performed by a blinded research assistant at the SC.

Other system data that was not captured in any of the databases included waiting times for certain processes (for comparison to model outputs) and time requirements for unscheduled visits for one process at the SC. Estimates by managers and staff were used as model approximations of these unscheduled visits. Where possible, queue lengths were determined using manual counts of diagnostic test requisitions or referrals.

The data for the current study is stored under password protection on a network of secure computers within the SC, and the linked database was built within this secure framework. Data entry is performed by clerical staff and non-physician providers at the SC. To maximize both data quality and quantity, regular meetings were held with SC staff to reinforce the purpose of the data collection, encourage accurate and timely data entry and to discuss any arising challenges. All data extraction was performed by the Information Technology Analyst at the SC and presented as de-identified data. Ethics approval was obtained from the University of Calgary Conjoint Health Research Ethics Board (Ethics ID: 23243).

Preliminary Analysis

A preliminary data review was undertaken to assist in the definition of performance measures and to provide some early insights into system performance for the purposes of

model validation (see *Verification & Validation* below). After discussion with SC managers, one important insight that arose from this analysis was the increase in queue lengths and waiting times over time. This finding had important implications for both the type of simulation analysis performed and the determination of performance measures (see *Model Performance Measures* below).

For both the base case and alternative scenarios, the estimated resource utilization for each process was calculated by dividing the estimated weekly demand (see *Input Data* in Chapter 5) by the estimated weekly capacity. Capacity for the physicians and the psychologist was estimated by using the weekly average number of clinic hours from the 2008-10 data. Since diagnostic test resources and alternate care provider (CPAP clinic) therapists were assumed to be always available, the current weekly capacity was used for these resources. Weekly demand was estimated by using the total number of each visit type in the entire visit history of all patients in the dataset. Demand was corrected for missed appointments by incorporating the no-show rate into the calculation. The estimation of demand for each process is demonstrated below:

For diagnostic testing (i.e. ambulatory or in-laboratory testing):

> Demand = # Arriving patients/week x (1-probability of no-show for test) x (# Tests in entire dataset/ # Patients)

For Provider visits (i.e. physician, psychologist or CPAP clinic):

Demand = # Arriving patients/week x (1-probability of no-show for test) x [(# All new visits for provider in entire dataset/ # Patients) x # Hours/new visit + (# All follow-up visits for provider in entire dataset/ # Patients) x # Hours/follow-up visit]

In addition to patient demand, the predicted weekly demand for the CPAP clinic included an estimate of "Professional Consult" work. This work includes clinical and clerical activities that occur outside of direct patient care, and is a significant component of a CPAP clinic therapist's daily duties.

Preliminary analysis was also attempted using an open queueing network (OQN) tool based in Microsoft Excel. The purpose of the OQN tool is to identify resource requirements for a series of process steps taken by a patient at the SC. Based on estimated routing probabilities from one step to another and the availability of each resource, the OQN tool can predict resource utilization and suggest areas of system congestion. Unfortunately, significant variability in patient flow pathways and different appointment lengths for different visit types precluded the determination of routing probabilities and resource requirements without a number of simplifying assumptions. The likelihood that these assumptions would compromise the accuracy of the estimated inputs was thought to be too high to continue with the OQN analysis.

Simplifying Assumptions & Approximations

The level of system detail that is captured in a model may vary depending on its objectives and intended purpose. Furthermore, some system data may be unavailable or incomplete. As a result, simplifying assumptions and approximations may be used. Often, simplifying assumptions are used in areas that are not expected to significantly impact a model's performance with respect to its purpose. Approximations may be varied to test their robustness within a model. A number of simplifying assumptions and approximations were made during model conceptualization and implementation. These were discussed with subject matter experts for accuracy and importance (see *Verification & Validation* below). A detailed list of and rationale for each of these assumptions and approximations is provided in a document entitled "Simplifying Assumptions for Foothills Sleep Centre DES Model" (Appendix C), and in a spreadsheet called "Approximations Summary for Foothills Sleep Centre DES Model" (Appendix D).

Model Conceptualization and Construction

The DES model was constructed using the Arena version 12 (Rockwell Automation Technologies, Inc., Wexford PA) software package. Given that arrival patterns, patient complexity or probability distributions for various model inputs could change over time, the model was designed with parametric inputs. As a result, changes to these parameters would allow the model to run with different input values, to permit sensitivity analyses. The conceptual model, which is the representation of the SC in the DES model (see *Verification & Validation* below), is presented in a document called "Model Purpose & Data Structure for Foothills Sleep Centre DES Model" (Appendix E). Further details of

the components of the model were summarized in a spreadsheet called “Model Components for Foothills Sleep Centre DES Model” (Appendix F). These documents facilitate the interpretation of model coding.

Patients were represented as entities in the model, while test resources and clinical providers were modeled either explicitly as resources or as model variables representing resource availability. Patient arrivals were represented as a Poisson random variable with arrivals occurring weekly. Arrivals were modeled as occurring simultaneously on the same day each week, rather than daily, after consultations with the triage coordinator revealed that referrals were not processed daily and that a weekly estimate was more appropriate. The mean number of arrivals for this Poisson distribution (51 patients/week) was based on the weekly average number of referrals from January 2008 to December 2010. As a patient entity arrived in the model, an index number corresponding to a patient record from the dataset was randomly selected. All patient records in the dataset had an equal probability of being assigned to a patient entity. This index number was used to assign patient characteristics to the arriving patient entity in the model, thus preserving the correlations between these characteristics within the model. The specific characteristics assigned using the index number included those which informed decisions about physician assignment (e.g. patient category based on likely diagnosis), queue priority (based on the triage urgency rating assigned at the time of referral or the urgency rating of a requisition for diagnostic testing), and any relevant delays that were due to patient factors (e.g. the time it took for a patient to return a screening questionnaire that must be returned before an urgency rating can be assigned for most patients). The index

number also corresponded to a sequence of visits that was used to direct patient entities through the model from referral until discharge. Depending on the path taken by the actual patient, these sequences ranged from a single visit to the SC for a test to multiple visits for testing and appointments with different clinical providers. For all clinical pathways corresponding to an index number, a visit type (e.g. new or follow-up, testing protocol) was assigned based on the type of visit taken by the patient in the actual system. Finally, the required delay between clinician appointments was incorporated into scheduling algorithms using information linked to the index number. The variables related to visits were read into the model before any patients entered the model.

At the SC, the list of physicians that can assess a new patient depends on the patient's suspected diagnosis, and the patient is scheduled to see the next available physician within that list. Although the actual patient visit history was used to determine the number, sequence and frequency of visits for patient entities assigned a given index number, the physician group with the earliest available appointment slot was assigned to the patient as a patient entity characteristic. The patient was then routed to the appropriate physician group based on this characteristic. As a result, the physician assigned to the patient within the model may have differed from the actual physician that assessed the patient. This modeling approach was thought to be more appropriate by subject matter experts (see *Verification & Validation* below). Additionally, physicians who had similar expertise and assessed similar patient types were represented as a single physician group with variable capacity rather than as individual providers. By modeling

physician availability in this way, provider capacities could be changed in model perturbations.

The main resources modeled corresponded to different processes at the SC. These included diagnostic tests (ambulatory sleep testing (SSAT) and in-laboratory polysomnography (PSG)) and clinician visits (CPAP clinic, four physician groups (respirologist, neurologist, OSA only physician, general internist) and a psychologist). Since diagnostic testing was scheduled in advance and there were no queues for unscheduled testing, equipment and personnel were represented in aggregate as available slots for testing. Similarly, physicians and the psychologist were also represented as the number of available time slots in a given day. CPAP clinic therapists were modeled as scheduled human resources, since this clinic provides both scheduled and unscheduled visits. Clerical staff and physical space were not modeled explicitly. As patients flowed through the model, they entered submodels for each visit. Within a submodel, the patients underwent appointment scheduling using known scheduling rules, waited for the appointment and proceeded to have the visit. All cancellations and no-shows also occurred within the submodels. In the actual system, patients who require testing and follow-up clinical visits have both appointments scheduled simultaneously. This linked appointment scheduling was not modeled explicitly in the current study due to the significant added complexity in doing so. In the DES model, patients were scheduled for an appointment after the previous visit was scheduled and completed. It was recognized that the model may systematically underperform as a result, but this simplification was

accepted as appropriate by the subject matter experts (see *Verification & Validation* below).

Once patient entities completed a visit, they emerged from the submodels and any relevant performance data pertaining to the visit was collected. The assigned visit trajectory was then evaluated to determine whether the patient should be routed through subsequent visits or discharged from the model.

Model Replication Parameters

Depending on the system being modeled and the purpose of the model, different types of simulation analysis are possible. For the purposes of analyzing changes in patient flowtimes and queues, the SC does not have a defined start and end time. Thus, a terminating analysis, in which the system starts with all resources available and no patients in system, was deemed inappropriate. Since the preliminary analysis revealed that the system was not in steady-state (see *Preliminary Analysis* above and *Analysis of Input Data: Actual and Predicted Utilization* in Chapter 5), a single long simulation run to provide steady-state data over time was also not justified. Thus, the method of truncated replications was chosen. This technique generates model performance data from multiple simulation runs of finite length, with data collection starting with the model in a state that is representative of the actual system (71).

The method of truncated replications requires either pre-loading of the model with patient entities and queues to approximate the real system or an initialization period during

which the model is allowed to become congested and for which all outputs are discarded. There are a number of techniques to determine the length of the initialization period (82). For the current study, 30 simulation runs of 3650 days were performed for the base case scenario. For these simulation runs, the total number of patients in the model and the queue lengths for all processes were graphed in an Arena application called the Output Analyzer. Although many of these outputs increased over time due to the lack of a steady-state, the rate of increase became stable after an initial inflection point. The simulation time at which this inflection point occurred was different for many of the performance measures. The longest of these simulation times was approximately 2000 days. Thus, an initialization period of 2000 days was selected. Since many patients wait for approximately 1.5 years from referral to initial assessment and subsequently may wait for another six months for advanced testing, it was determined that three years (1095 days) of data collection would be required to ensure that patients would reach the specified outcome visits. Thus, the replication length was set at 3095 days. Fifty simulation replications were performed for each scenario to approximate a normal distribution for the replication means.

Verification & Validation

Verification and validation (V&V) are two processes to determine a model's usefulness. During model conceptualization and implementation, V&V is an iterative process that occurs with each version of the model. The paradigm underlying V&V involves interactions between the system under study, the input data, the conceptual model and the

computerized model. V&V can be performed by the modeling team in conjunction with system stakeholders or independent verification and validation (IV&V) can be performed by a third party. IV&V is appropriate for large-scale simulation projects involving multiple modeling teams or for problems for which solutions may have a high cost (83). In the current study, only one team performed all simulation modeling and analysis, and the expected associated costs were minimal. Furthermore, although model detail was extensive, the scope of the project did not warrant the third party involvement. Thus IV&V was not performed.

Verification involves an examination of the model to ensure that it has been correctly constructed; it is an assessment of whether the coded model performs as desired, and is independent of the system being modeled (84). The DES model of the SC was verified using a number of established verification techniques (71), which are described below:

- Modular modeling – as described above, the processes within the DES model were constructed as separate submodels. Each submodel was verified in isolation before all submodels were combined in the larger model. Furthermore, more complex aspects of the system were added only after a simpler form of the combined model was verified.
- Model review by DES experts – structured walkthroughs were not performed as part of model verification. However, submodels and specific areas of model code were reviewed individually with two members of the supervisory committee who have extensive experience with DES.

- Variation of input parameters – simulation runs were performed under a variety of input settings to examine whether the resulting outputs changed as expected. These included changing arrival rates or resource availabilities to monitor the effects on model congestion, assigning all arriving patient entities the same attributes to evaluate the coding of specific subprocesses and clinical pathways, and changing cancellation or no-show probabilities to assess the effects on model performance.
- Interactive debugging – the Arena software package contains an application called the Run Controller. This application allows the modeler to list or 'trace' state variables in the model during a run, such as queue lengths, resource capacities, or patient characteristics. The Run Controller can also be used to follow a single patient entity through the model, or to pause the simulation immediately before a particular model component executes its function. State variables can be changed at various points in the simulation run to determine whether the model or model component behaves as expected under a variety of conditions. All the above techniques were used within Arena's Run Controller to verify model implementation.
- Animation – rather than reviewing simulation code directly, an animated version of various model components can be used to ensure that the model is behaving as desired. A 'Dashboard' presenting numerical values for a number of dynamic state variables was constructed within the DES model. Variables presented on the Dashboard included the current simulation date, queue lengths, provider and test

availability, and a breakdown of different visit types for each test or provider. During the simulation run, these variables were inspected for congruence with expected model behaviours.

Validation is the comparison of the model to the real system; while no model can perfectly represent the system of interest, validation ensures that the degree of accuracy is consistent with the intended applications of the model (83). Validation techniques used in the current study included:

- Regular meetings with individual SC managers and staff
- Formation of a 'Sleep Expert Panel' (SEP), composed of three sleep physicians and two SC managers
- A single meeting with administrators from Alberta Health Services (AHS), who oversee operational and budget decisions for the SC

Validation of the DES model was divided into data validation, conceptual model validation and operational validation (83), each of which is discussed below:

- Data validity – where possible, recent historical patient data from the clinical and administrative databases was used (see *Data Collection and Input Data* above). Initial database queries were reviewed with SC staff to identify discrepancies or outliers, and any missing data was obtained retrospectively from patient charts by SC staff or the research assistant. If required data was unavailable from database queries or chart review, estimates were obtained from subject matter experts.

Visit frequencies from the dataset were compared to visit frequencies from historical clinic data to ensure that the input data was representative of system data. Additionally, system statistics related to individual processes (e.g. appointment cancellation rates, percentage of CPAP clinic visits conducted by telephone) were also reviewed with subject matter experts and thought to accurately represent system parameters.

- Conceptual model validation – a conceptual model is the mathematical and verbal representation of the system that includes a description of the driving data structure and any simplifying assumptions and approximations. Conceptual model validation provides the assurance that this representation is adequate for the purposes of the model. Face validation of the model was performed through regular meetings with the SEP and structured walkthroughs of aspects of the DES model with SC staff and managers.
- Operational validation – a model that represents an observable system can be operationally validated through comparisons to actual system data. Such comparisons include subjective review with subject matter experts and more objective comparisons such as statistical analysis or Turing tests (71,83). However, due to difficulty satisfying statistical assumptions and problems with the accuracy or completeness of existing system data, statistical hypothesis testing of model and system data is often not possible (83). In the current study, the unavailability of reliable operational performance data precluded direct comparisons between model and system data. Although the database was

modified to collect such data, the long delay between referral and assessment for most patients did not allow for this data to be used in the current study. Output data was reviewed with the SEP as a group and individually, and was thought to reflect actual system performance. Turing tests and other objective comparisons of model and system data were not performed.

Model Perturbations

A key advantage of simulation modeling is the ability to perturb the model to gain insights into the effects of system changes on system performance. A series of model perturbations was pre-specified, with the recognition that additional alternative scenarios could be determined based on the performance of the base case scenario. Possible system changes were also solicited from AHS administrators and the SEP. Based on this input, the following perturbations (with abbreviations) were modeled for comparison to the base case model:

- Elimination of prioritization by the urgency rating assigned at the time of referral (NoTriage)
- Elimination of an alternate care provider clinic that exists for patients with sleep-disordered breathing (SDB), with conversion of these visits to physician visits (NoCPAP)
- Addition of 1 clinic per week of physician capacity for the physician group with the longest queue length at the end of the simulation, averaged over all simulation runs (AddMD)

- Addition of respiratory therapy (RT) capacity by 0.5 full-time equivalents (FTE) in the alternate care provider clinic (AddRT)
- Addition of both 1 physician clinic per week and RT capacity by 0.5 FTE (combination of scenarios 3 and 4 above) (AddMD_RT)

It was expected that the first two alternatives would adversely affect model performance, thus demonstrating the benefit of these system components. In particular, the NoTriage scenario was proposed to prove that a prioritization system would be required to ensure timely access for urgent patients. Since alternate care provider clinics are not common at sleep centres, the NoCPAP scenario was intended to highlight the importance of the CPAP clinic as an effective adjunct to physician care. The latter three configurations were expected to improve model performance in that they all involved the addition of resource capacity to important and congested processes at the SC.

Each alternative configuration was constructed in a separate DES model to permit the use of alternative patient flow pathways or different input data in the NoTriage and NoCPAP scenarios. Thus, a perturbation was implemented at the beginning of the simulation, rather than after a common initialization period under base case conditions. Using this approach, it was recognized that the comparison of absolute performance measures after a period of initialization might be partially influenced by the state of each model at the end of the initialization period rather than model performance over the simulation itself. Essentially, this approach to comparing model configurations demonstrated how the system might have performed if it had been designed differently from inception, rather

than if an existing system was modified. To attempt to compare the performance of the models during the period of data collection, an outcome describing the change in a model output over time was deemed necessary.

The same initialization period (2000 days) was used for all model configurations. It was recognized that if alternative model configurations performed differently, the initialization periods could also differ, thus making the interpretation of model outcomes difficult. For example, if an alternatively configured model was initialized much earlier than 2000 days, any outcomes that increased over time would appear worse than the base case scenario if measured at a specific time in the simulation. In contrast, if initialization was not complete by 2000 days, model congestion could be inadequate and result in underestimates of these outcomes. A conservative initialization period was used to mitigate the potential for incomplete loading of the model. Additionally, it was recognized that a comparison of the change in a model output over time could be used to fairly compare models with different initialization periods.

The main implication of using separate DES models to compare each perturbation was that policy decisions based on changing an existing system could not be made from the results of the current study. The numerical results of the current study were expected to differ from that of a single model incorporating changes to an existing system, as discussed above. However, it was recognized that more qualitative conclusions about the performance of model perturbations could be drawn, providing a foundation for further comparisons using a single model.

Model Performance Measures

Preliminary data analysis and meetings with subject matter experts revealed that waiting times had increased over approximately two years prior to the initiation of the current study. Thus, outcomes that assumed steady-state system performance were deemed inappropriate for the DES model. Rather, an outcome measure that incorporated the time that it was measured was determined to be necessary.

Discussion with the SEP revealed that the most important point in a patient's visit trajectory is the initiation of treatment. Thus, the primary outcome measure was the mean time taken for a new patient to flow through the system from referral to initiation of treatment (T_{Treat}), measured for patients initiating treatment in the last month of each simulation run. Since specific treatments were not recorded in the databases, treatment initiation was defined as:

- The first follow-up physician visit after an initial physician visit
- The first visit to a psychologist clinic for insomnia
- The first visit to an alternate care provider clinic for SDB

To examine the effects of model perturbations on T_{Treat} over time, the percent change in T_{Treat} between the first and last months of the simulation was also measured. All remaining secondary outcomes were analyzed during the last month of the simulation only. These performance measures were:

- The time to initial physician visit for all patients ($T_{Initial}$)

- The time to advanced diagnostic testing for those that required it (T_{PSG})
- The percentage of patients with SDB who met the Canadian Thoracic Society's (CTS) maximum waiting time recommendation of 180 days (85)

Subgroup analysis was performed by triage urgency status for T_{Treat} and $T_{Initial}$, and by the urgency of the PSG request for T_{PSG}. The CTS guidelines classify patients as high-risk if they have a safety-critical occupation, certain comorbidities or severe SDB (defined by a sleep test showing at least 30 respiratory events/hour), and recommend a maximum delay to assessment of 30 days (85). A subgroup analysis of the adherence to CTS guidelines was performed for patients with the first or last of these high-risk criteria, since data limitations precluded the collection of comorbidity data. It was recognized that this result would represent an overestimate of actual system performance with respect to these high-risk patients.

T_{Treat} was also analyzed by SDB status. Although the databases did not include information on clinical diagnosis, the differentiation of outcomes by SDB status was deemed to be clinically relevant. Patients were classified as having SDB if they met at least one of the following criteria:

- An ambulatory sleep test (SSAT) showing at least 15 respiratory events/hour
- An in-laboratory sleep test (PSG) showing at least 15 respiratory events/hour
- An assessment by the alternate care provider clinic for patients with SDB

All performance measures were evaluated using the arrival pattern calculated using 2008-2010 data (see *Model Conceptualization and Construction* above).

Increased Demand Case

The simulation runs were repeated with a 5.06% increase in the average weekly number of arrivals (Increased demand case). This value represents the actual growth in the population of the City of Calgary from 2007 to 2010 (86). It was assumed that the case mix of referrals would not change despite higher demand volumes.

Statistical Analysis

To ensure that the visit trajectories of patients in the input dataset were representative of the cohort of patients referred in 2007, a sample size calculation was performed. Since this cohort included patients whose charts were no longer active (no visits since January 1, 2009) and patients who were still active (at least one visit after January 1, 2009), the least frequent trajectory was determined for each subset. To obtain a representative sample, a sample size calculation was based on a comparison of the lower of these two frequencies to zero. The least frequent visit path was the completion of testing without a physician visit for patients in the active group. The frequency of this trajectory was 4.97%. Using a two-sided alpha of 0.05 and a power of 0.9, a sample size of 75 patients was calculated. However, it was also determined that sampling approximately 10% of patient charts from the cohort of referrals would be ideal. Thus, a sample of 150 charts was obtained for the dataset.

When comparing alternative configurations of a stochastic model, the variance of simulation results reflects both the changes in performance from model perturbations and the randomness of outputs from the use of random inputs. The latter, also known as 'output variance', may threaten the precision of the study results. Output variance can be reduced using a variety of variance reduction techniques, the most common of which is the use of common random numbers (CRN) (82). In this method, important random distributions are assigned random number streams that differ from the default stream. To create similar experimental conditions for each scenario, the same random number stream is used for the same random distributions within each configuration of the model, a process called synchronization. Common random numbers were used for the random number of weekly arrivals and were synchronized across scenarios.

Statistical analysis of model outputs was performed using the method of "comparisons to a standard" (71). For each of k model configurations, the mean of an outcome measure over all replications is calculated. The difference between the mean for each alternative scenario (μ_i) and the base case configuration (μ_1) is compared to zero. The null hypothesis (H_o) and alternative hypotheses (H_A) for each comparison are as follows:

H_o: $Z_i = 0$

H_A: $Z_i \neq 0$

Where $Z_i = \mu_i - \mu_1$ for all i from 2 to k

A confidence interval is calculated for each Z_i using a paired-t approach. A statistically significant difference exists if the confidence interval does not include zero. For the primary outcome, there were 6 scenarios (including the base case), thus resulting in 5 confidence intervals for Z_i. To minimize the increased probability of Type I error from multiple comparisons, a Bonferroni correction of the desired alpha level was performed as follows:

Desired $\alpha = 0.05$

Corrected $\alpha = 0.05/5 = 0.01$

Thus, to obtain an overall Type I error rate of 0.05 for the primary outcome, a 99% confidence interval was calculated for each comparison. Secondary outcomes, subgroup analysis by urgency category and SDB status, and the increased demand case were also analyzed in this way, using a 99% confidence interval. The method of "comparisons to a standard" with a Bonferroni correction is valid in the setting of variance reduction techniques such as CRN.

Chapter 5: Analysis of Input Data and Model Results

Analysis of Input Data: Descriptive Statistics

Queries of the Clinic Information System (CIS) revealed that in 2007, 2249 patients were entered into the database. Of these, 667 (30%) had no visits and were excluded. Of the remaining 1582 patients, 442 had visited the Foothills Sleep Centre (SC) since January 1, 2009 and were considered active, whereas 1140 were inactive. Forty patients were randomly selected from the list of active charts and 110 from the list of inactive charts. These 150 patient records formed the input dataset for the discrete-event simulation (DES) model.

Clinical information used at the referral and triage process for patients in the dataset is presented in Table 1. No data on sleepiness, occupation or urgency was available on thirty-five patients (23%) who did not arrive through the referral and triage process. Eleven out of 115 patients (10%) referred through the referral and triage process were deemed as "Primary Urgent" based on the initial referral information, and 27 (23%) were classified as "Secondary Urgent" based on referral and questionnaire data. Patients with a safety critical occupation (e.g. commercial truck driver, heavy machinery operator, airline pilot, etc.) comprised 8% of the dataset. The mean Epworth Sleepiness Scale score was 11, indicating mild excessive daytime sleepiness. Information on medical history, medications and final sleep diagnosis was not available for all patients. However, the patient type, which is based on likely sleep diagnosis and past medical

history, was available and is also presented in Table 1. The patient type is used to assign an appropriate provider during the referral and triage process.

Visit frequencies for both patients in the dataset and for all patients from January 1, 2008 to August 31, 2010 are shown in Table 2. This table lists the frequency of visits for each process in the system, as a percentage of visit type (e.g. Polysomnography (PSG) as a percentage of all tests, psychologist visits as a percentage of all provider visits). As a proportion of all tests, the frequency of PSG (35%) and ambulatory sleep tests (SSAT) (65%) did not differ from the 2008-10 historical data. There were fewer alternate care provider (CPAP clinic) visits in the dataset (28% vs. 37%, $p<0.001$). Conversely, visits to physicians seeing only patients with obstructive sleep apnea (OSA) were overrepresented in the dataset (13% vs. 8%, $p<0.001$), and a similar trend was seen for respirologist visits (35% vs. 29%, $p=0.008$). The percentage of appointments that were cancelled or visits that were missed by the patient, which differed depending on the process, is given in Table 3. These ranged from approximately 10% to 40% for cancellations, and from approximately 2% to 8% for missed appointments.

Fifty-three of the 150 patients (35%) in the dataset did not have a visit that met the pre-specified definition of treatment initiation. Thus, the time to initiation of treatment could not be calculated for entities representing these patients in the model. The exclusion of this large proportion of patients from the measurement of the primary outcome was reviewed with the sleep expert panel (SEP). The consensus of the SEP was that for most patients, the visit at which treatment was initiated was the most important visit for a

patient. Additionally, the SEP agreed that measuring the time required to reach a visit in the middle of the patient's visit trajectory (i.e. not the first visit) was important to capture the complexity of the SC in the model. Fifty-two (35%) patients had at least one PSG and 120 (80%) had at least one physician visit. Eleven of the 150 patients (7%) did not have a visit that satisfied at least one of the study outcomes.

Descriptive statistics of the dataset corresponding to study outcomes are presented in Table 4. The average time to treatment was 266 days for all patients, 100 days for urgent patients, and 246 days for patients with sleep-disordered breathing (SDB). The average time to an initial physician visit was 222 days for the entire cohort, and 58 days for urgent patients. On average, the time from the visit prior to a PSG until the PSG was completed was 46 days for all patients and 30 days for urgent patients. This delay included the time until the test was completed and did not include any delay associated with PSG interpretation. Sixty-one percent of patients with SDB met Canadian Thoracic Society (CTS) guidelines for initial assessment, whereas only 7% of high-risk patients met the corresponding CTS guideline of 30 days. The standard deviation for each of these measures revealed considerable variability, and the number of urgent patients meeting outcomes was small.

Analysis of Input Data: Actual and Predicted Utilization

The mean arrival rate was determined to be 51 patients per week. Based on this average arrival rate, the actual clinic capacity and approximations of average service rate for new and follow-up patients, utilization estimates for PSG (1.14), respirologists (1.27) and

physicians seeing only OSA patients (1.59) were greater than one. This finding confirmed that the SC was not a steady-state system (see *Queueing Theory and DES* in Chapter 3). Furthermore, the estimated utilizations for the SSAT process, CPAP clinic and psychologist were 0.93, 0.91 and 0.96, respectively. These utilization estimates are provided in Table 5 under the heading "BaseCase".

Spreadsheet analysis of predicted utilization under the proposed alternative scenarios is also shown in Table 5. The elimination of the CPAP clinic increased the predicted utilization for all providers except the neurologist, and resulted in a predicted utilization greater than one for the general internist physician (1.16) and psychologist (1.01). The base case simulation revealed that the respirologist process had the longest average queue length at the end of simulation, resulting in the addition of a weekly respirologist clinic for the AddMD scenario. The resulting change in the respirologist utilization was a decrease from 1.27 to 1.11. When respiratory therapist (RT) capacity was added to the CPAP clinic, the estimated CPAP clinic utilization decreased from 0.91 to 0.76. The addition of both respirologist and RT capacity reduced the predicted utilization for the respirologist and RT to 1.11 and 0.76, respectively.

Base Case Model Performance

The results of the base case simulation runs are presented in Table 6. Simulation results demonstrated with 99% confidence that the mean time to treatment initiation in the last month was between 253 and 274 days. T_{Treat} increased by 25% to 35% over the three year simulation period, which supported the assessment from the preliminary data

analysis and process description that the SC was not a steady-state system. The 99% confidence interval (CI) for the time to the initial physician assessment was 193 to 207 days. Subgroup analysis revealed that urgent patients had shorter than average waits for an initial physician assessment (156 to 173 days) although the estimated time to treatment was longer (374 to 420 days). For patients with SDB, the time to treatment initiation was between 213 and 231 days with 99% confidence. The estimated time to initial PSG was between 145 and 163 days, whereas patients whose PSG was requested urgently waited significantly less than average for their PSG (59 to 60 days). Between 53% and 60% of patients with SDB were assessed by a provider within 180 days according to CTS guidelines, but the 99% CI for the percentage of high-risk patients meeting the CTS guideline of 30 days was only 5% to 9%. The physician group with the longest queue at the end of the simulation was the respirologist group (mean 484 patients); thus, one extra weekly clinic was added to the RespMD resource for the AddMD and AddMD_RT scenarios.

The base case results for T_{Treat} and $T_{Initial}$ were similar to the corresponding values observed for the dataset (see Tables 4 and 6). These model outcomes were significantly higher than the values obtained from the dataset for urgent patients, but T_{Treat} for patients with SDB was comparable in the model and dataset. The time to initial PSG was higher in the model for all patients and for urgently requested PSGs, although the model incorporated a delay of 30 days for scoring and interpretation, In the model, adherence to CTS guidelines did not differ from the values observed in the dataset for all patients with SDB or for high-risk patients.

Primary Outcome: Time to Initiation of Treatment (T_{Treat})

The results of model perturbations on the primary outcome (T_{Treat} in the last month) are shown in Table 7 and Figure 2. Elimination of triage prioritization for patients improved this outcome by 30 to 56 days with 99% confidence, and the addition of a respirologist clinic decreased T_{Treat} by 60 to 84 days. Marked deterioration was seen when the CPAP clinic was removed, resulting in an increase in the estimated T_{Treat} of between 387 and 441 days. The addition of an RT to the CPAP clinic did not change model performance, whereas the addition of both physician and RT capacity improved performance to a similar extent as adding a physician only (99% CI of 58 to 81 days). The mean number of patients reaching the primary outcome was between 118 and 124 for all scenarios except the NoCPAP scenario, for which the average number of patients initiating treatment was 92.

Subgroup analyses of T_{Treat} for urgent patients and for patients with SDB are presented in Table 8. Simulation results revealed that the addition of physician capacity reduced the estimated time to treatment initiation in urgent patients by 119 to 185 days with 99% confidence. The improvement in T_{Treat} was between 115 and 173 days when both physician and RT capacity were increased. These improvements in access for urgent patients were greater than for all patients combined. Similarly, the adverse effect of the removal of the CPAP clinic was amplified in urgent patients, with a 99% CI of 610 to 727 days. Neither the removal of the triage system nor the addition of RT capacity had any effect. Eight urgent patients initiated treatment in the last simulated month in the

NoCPAP configuration, compared to mean values of 10-12 patients in the other scenarios.

Table 8 also reveals the results for patients with SDB, in whom an improvement of between 27 and 55 days was seen with the removal of triage prioritization. The addition of physician capacity also improved T_{Treat}, with a 99% CI of 62 to 83 days. A marked deterioration in model performance resulted from elimination of the CPAP clinic (504 to 582 days), and adding an RT had no effect. The addition of both a physician clinic and RT capacity decreased T_{Treat} by 57 to 79 days, with 99% confidence. On average, this outcome was measured in fewer patients with SDB in the NoCPAP scenario (38 patients) than in the other scenarios (77-80 patients).

Secondary Outcome 1: Change in Time to Treatment Initiation

With 99% confidence, the percent change in T_{Treat} over the three year simulation period increased by 4% to 25% when the triage system was removed from the DES model. When the CPAP clinic was eliminated, the change in T_{Treat} was 2% to 19% higher. Neither the addition of a respirologist clinic, addition of RT capacity, nor the addition of both significantly affected the change in T_{Treat}. The results of model perturbations on this outcome are shown in Table 9 and Figure 3. None of the alternative scenarios resulted in a 99% CI for the change in T_{Treat} that included zero, suggesting that the model did not enter a steady state under any configuration.

Secondary Outcome 2: Time to Initial Physician Visit ($T_{Initial}$)

The effects of the alternative scenarios on $T_{Initial}$ in the last month are presented in Table 10 and Figure 4. Similar to the primary outcome, the elimination of triage urgency (44 to 62 days), the addition of physician capacity (72 to 89 days), and the addition of both physician and RT capacity (68 to 84 days) improved the time to the initial physician visit with 99% confidence. Conversely, the removal of the CPAP clinic worsened the estimated time to an initial physician visit by 275 to 300 days. The addition of RT capacity did not change model performance with respect to this outcome. The mean number of patients reaching $T_{Initial}$ in the last month was between 156 and 160 for all configurations except the NoCPAP scenario, in which an average of 141 patients reached this outcome.

As is shown in Table 11, model perturbations had a similar effect on the estimated time to initial physician visit for urgent patients as for all patients. When the CPAP clinic was removed, $T_{Initial}$ increased by 395 to 439 days, but a decrease of 116 to 135 days was observed when physician capacity was increased either alone or in combination with the expansion of RT capacity. No change in model performance was seen when the triage process was removed or when RT capacity was added in isolation. The average number of urgent patients with an initial physician visit ranged from 12 to 16 patients.

Secondary Outcome 3: Time to Initial Polysomnography (T_{PSG})

The results of model changes on the estimated time to initial PSG are provided in Table 12 and Figure 5. With 99% confidence, the addition of physician capacity increased T_{PSG} by 49 to 77 days, and the removal of the urgency rating at the referral and triage stage

increased it by 17 to 52 days. In contrast, the elimination of the CPAP clinic reduced T_{PSG} significantly, with a 99% CI of 105 to 124 days. The addition of RT capacity did not affect this outcome in isolation, and was not significantly different from the AddMD scenario when combined with increased physician capacity (59 to 87 days). On average, 62 to 67 patients contributed to the measurement of this outcome.

Subgroup analysis of patients for whom PSG was requested urgently is shown in Table 13. Compared to the base case estimate of 59 to 60 days, no change was seen with any model perturbations except for the elimination of the CPAP clinic, which improved the time to initial PSG by approximately 45% (99% CI of 25 to 27 days). Between 26 and 29 patients with urgently requested PSG tests had a PSG in the last month of simulation.

Secondary Outcome 4: Adherence to Waiting Time Guidelines

The elimination of prioritization by urgency improved the percentage of patients meeting Canadian Thoracic Society (CTS) guidelines by 16% to 28% with 99% confidence. Guideline adherence was also improved by 33% to 40% with the addition of a weekly respirologist clinic. The removal of the CPAP clinic resulted in 14% to 24% fewer patients being assessed within the recommended time of 180 days, while the addition of an RT to the CPAP clinic had no effect. The addition of both respirologist and RT capacity increased the estimated percentage of patients meeting CTS guidelines by 31% to 39%. The results of model perturbations for this outcome are shown in Table 14 and Figure 6. The mean number of SDB patients with an initial provider visit in the last month was between 70 and 73 for all scenarios except NoCPAP (52 patients).

With 99% confidence, the adherence to CTS guidelines for high-risk patients with SDB was only 5% to 9%. This poor performance deteriorated further in the NoCPAP scenario, in which no patients met this target. As is demonstrated in Table 15, none of the other model perturbations affected the percentage of patients meeting the high-risk target of 30 days. Thirty-two high-risk patients with SDB had an initial provider visit in the last month in the NoCPAP configuration, whereas 39 to 41 patients had an initial visit in all other configurations.

Queue Lengths

The queue lengths at the end of simulation for the different model processes are presented in Table 16. These queues represented patients waiting to be scheduled for an appointment and did not include patients who were scheduled but whose appointment date had not yet arrived. Under the base case scenario, the largest mean queue lengths were seen at the respirologist (484 patients) and PSG (315 patients) processes. The queue lengths for the other physicians and SSAT process were below 20 in the base case scenario. The queue for the CPAP clinic contained no patients since there was an infinite appointment scheduling horizon for this process.

Table 16 also shows the changes in mean queue lengths at the end of simulation under different model configurations. When prioritization by triage urgency was removed, the average PSG queue increased from 315 to 443 patients (41% increase) while the respirologist queue decreased from an average of 484 patients to an average of 280 patients (42% decrease). The average length of the neurologist queue also grew when the

triage process was removed, increasing from 13 to 83 patients (5.38-fold); a lesser increase from 3 to 16 patients (4.33-fold) was observed for the general internist under this model configuration. A marked increase in the respirologist queue was seen when the CPAP clinic was removed (mean 4385 patients, 8.06-fold), with less dramatic increases in the queue lengths for the neurologist (70 patients, 4.38-fold) and general internist (12 patients, 3-fold). Adding a respirologist clinic significantly reduced the respirologist queue to an average of 5 patients (99% decrease), while the mean PSG queue increased to 543 patients (72% increase). The addition of an RT did not significantly change queue lengths compared to baseline, and the mean queue lengths with addition of an RT and a physician clinic were not different from the AddMD scenario alone. The queue lengths for all other processes did not change significantly under any scenarios. Notably, the total number of patients in queue for all processes was much greater in the NoCPAP configuration than in the BaseCase scenario. Conversely, this total was decreased compared to the BaseCase value in the AddMD and AddMD_RT configurations.

Increased Demand Case

Based on population growth estimates for the City of Calgary, simulations were repeated with a 5.06% increase in the weekly number of arriving patients. Specifically, the mean for the Poisson arrival distribution was increased to 53.58. The results of the base case scenario with this increased demand are compared to the baseline arrival pattern in Table 17. Compared to no increase in demand, the time to treatment initiation in the last month was approximately 100 days longer overall as well as for urgent patients and patients

with SDB. The change in the time to treatment initiation did not worsen significantly. With 99% confidence, the time to initial physician visit increased by 78 to 99 days overall, and by 25 to 51 days for urgent patients. While the time to first PSG increased by 36 to 67 days overall, no deterioration was seen for patients whose PSG was requested urgently. The 99% CI for the percentage of patients meeting waiting time guidelines worsened overall (22% to 30%). No high-risk patients met CTS guidelines in the increased demand case.

Simulation results for each alternative scenario in the increased demand case are presented with the baseline demand results in Figures 2-6. Additionally, the comparisons of model performance for the alternative scenarios are shown in Tables 18-22. For the time to treatment initiation in the last month, alternative scenario performance was similar to performance with the baseline arrival rate. As is shown in Table 18, the NoTriage (99% CI of 18 to 51 days), AddMD (56 to 84 days) and AddMD_RT (49 to 79 days) scenarios improved T_{Treat}, whereas the NoCPAP scenario worsened it dramatically (348 to 412 days).

With 99% confidence, the change in T_{Treat} increased by 2% to 20% above baseline with the elimination of triage, and by 2% to 16% with the addition of RT capacity. In contrast to the baseline arrival rate, the removal of CPAP clinic did not significantly affect this outcome. The addition of a physician clinic, alone or in combination with RT capacity, had no effect on this outcome (see Table 19).

Table 20 shows that the time to initial physician visit was similarly affected by alternative configurations in both the baseline and increased arrival simulations. Specifically, the NoTriage (99% CI of 34 to 56 days), AddMD (73 to 91 days) and AddMD_RT (68 to 86 days) scenarios resulted in reduced delays to initial physician assessment. In contrast, the elimination of the CPAP clinic caused a deterioration in $T_{Initial}$ of 256 to 286 days, with 99% confidence.

The effects on time to first PSG are presented in Table 21. Similar to the baseline arrival rate, NoTriage (99% CI of 10 to 46 days), AddMD (39 to 69 days) and AddMD_RT (49 to 85 days) increased the time to initial PSG. A greater reduction in this outcome was seen with the elimination of the CPAP clinic (153 to 177 days) with increased arrivals, as compared to a reduction of 105 to 124 days with the baseline arrival rate.

The percentage of patients meeting CTS guidelines was affected differently by alternative scenarios when demand was increased. As in the baseline arrival rate simulations, Table 22 demonstrates that with 99% confidence, this outcome improved by 10% to 19% when physician capacity was added, and by 9% to 19% in the AddMD_RT scenario. However, neither the removal of prioritization by urgency, elimination of the CPAP clinic, nor the addition of RT capacity alone had a significant impact on this outcome.

Table 16 shows that the mean queue lengths at the end of the simulation runs were greater with the increased demand case compared to scenarios for the baseline arrival rate. In the base case scenario, the mean queue length for the SSAT process increased by 380 patients. Similarly, the queues for the respirologist and PSG processes increased by

260 patients and 170 patients, respectively. Queues for the other physician groups also grew with increased demand, but to a lesser extent than the SSAT, respirologist and PSG processes. Since the CPAP clinic has an infinite scheduling horizon, the queue length did not increase when the demand was increased. The psychologist queue also did not increase. Additionally, alternative model configurations resulted in similar queue length changes as were observed with the baseline arrival rate.

Tradeoff Curves

Analysis of model performance under different model configurations revealed that improved times to initial assessment and treatment initiation were associated with longer delays to initial PSG. Additionally, the behaviour of the average queue lengths for PSG opposed that of mean queue lengths for the respirologist process under different scenarios. Tradeoff curves were constructed to demonstrate the relative changes in queue length for each scenario. These curves demonstrate the inverse relationship between T_{Treat} and T_{PSG} and between $T_{Initial}$ and T_{PSG}, and are shown in Figures 7 & 8. In particular, the dramatic increase in T_{Treat} and $T_{Initial}$ seen in the NoCPAP scenario was associated with a significant decrease in T_{PSG}. Conversely, the reductions in T_{Treat} and $T_{Initial}$ observed in the NoTriage, AddMD and AddMD_RT scenarios were associated with less marked increases in T_{PSG}. As is discussed above, the results in the model with the addition of RT capacity did not differ significantly from the base case scenario on either tradeoff curve.

A tradeoff curve was also constructed to evaluate whether the changes in T_{Treat} were associated with a deterioration in $T_{Initial}$. This curve is shown in Figure 9, and demonstrates that the implementation of alternative scenarios in the model had similar effects on both of these outcomes.

Post-hoc Comparison of Utilization Estimates

The utilization estimates from the input data and DES model can be compared as part of model verification. Since the system and model were not in steady-state, this comparison was not performed initially. However, after discussion with two modeling experts on the supervisory committee and after all the above data analysis was complete, the model was reconfigured to collect statistics on total resource capacity, work performed by each resource, and wasted resource capacity. Additionally, the arrival rate was reduced to 20 patients per week, which decreased all utilization estimates in the input dataset to less than 95%. At these utilization levels, preliminary runs suggested that queues were not exploding, and thus that the system was in steady-state. A single, long simulation run of 14000 days (after a 2000 day initialization period) was performed to gather statistics on resource utilization over an extended period of time.

The results of the utilization estimates from the dataset and from the model are presented in Table 23. The utilization predictions from the model were similar to those calculated from the dataset for the SSAT (38.3% vs. 36.6%), PSG (45.7% vs. 44.9%), CPAP (79.1% vs. 73.6%) and psychologist (39.9% vs. 38.0%) resources. However, the utilization predictions for the physician groups differed from model estimates. This result was seen

despite the calculation of pooled utilization, which accounted for the fact that patients in the model were assigned to the next available physician rather than the one who assessed them in the actual system. Further exploration revealed that the model coding for the probability that a physician would cancel a clinic in the future underestimated the actual cancellation probability from the historical data. Thus, utilization estimates from the model were lower than what was expected from the dataset calculations due to overestimated physician resource capacity. Recognizing the limitations posed by this modeling issue, the clinic cancellation probabilities were adjusted in the model such that the desired actual cancellation probabilities were achieved. The physician utilization estimates from the model and dataset were similar after this adjustment (41.2% vs. 46.6%), supporting the veracity of the remainder of the model.

Chapter 6: Discussion

Summary of Results

The current study demonstrated the impact of a number of operational policies on access to treatment in a representative discrete-event simulation (DES) model of the Foothills Sleep Centre (SC). The elimination of an alternate care provider clinic (CPAP clinic) for patients with sleep-disordered breathing (SDB) resulted in a marked deterioration in model performance. In contrast, a 'first-in, first-out' queueing policy for patient visits appeared to improve access overall but not for urgent patients. The addition of physician resources to bottleneck areas in the model also improved access. Augmentation of respiratory therapists to the alternate care provider clinic had no effect on model outcomes. Measures of access were based on recommendations by subject matter experts and current clinical practice guidelines.

Elimination of Urgency Rating (NoTriage)

In the current study, the mean time to treatment initiation (T_{Treat}) decreased by 43 days when prioritization by urgency was removed. Similar improvements were seen in the time to initial physician visit ($T_{Initial}$), and 22% more patients with SDB met Canadian Thoracic Society (CTS) guidelines for initial assessment. These findings are consistent with criticisms of prioritization strategies, which attribute the resulting system underperformance to increased demand variation (see *Queueing Theory and DES* in

Chapter 3). Additionally, the 'carving out' of resource capacity for higher priority patients may waste resources if such a patient is not available (87).

The NoTriage scenario was also associated with a 35 day mean increase in the time to initial polysomnography (PSG). This finding is not surprising, as the improvement in the access to initial assessment would be expected to result in patients arriving at the PSG process more quickly. Furthermore, the changes in queue length with the NoTriage configuration demonstrate that the bottleneck of the model shifted from the respirologist to the PSG process.

Subgroup analysis revealed an improved time to initial assessment and treatment initiation for patients with SDB, and that urgent patients by the SC's triage criteria did not have a longer waiting time than in the base case scenario. Since non-urgent patients might have been scheduled ahead of urgent patients in this model configuration, it would be expected that an additional delay would result for urgent patients. However, it is possible that the overall improvement in patient flow resulting from elimination of the urgency rating offset this delay. Another factor that could have contributed specifically for T_{Treat} relates to the fact that urgent patients in the dataset were more likely to undergo PSG testing; the added delay for PSG may have negated the efficiency gains from this model configuration. The relative contributions of these factors are unclear.

The adverse effect of the NoTriage scenario on the change in T_{Treat} over the simulation suggests that the beneficial effects of this configuration on model performance would not be sustained. This result suggests that over the longer term, system congestion would

overcome the efficiencies gained from eliminating prioritization strategies altogether. Further support for this finding was seen in the increased demand case, where the NoTriage configuration did not result in more SDB patients meeting CTS guidelines.

It is important to acknowledge that the level of detail in the DES model likely influenced the comparison between the BaseCase and NoTriage scenarios, specifically with respect to the treatment of urgent patients. In the base case scenario, patients were assigned to the physician with the next available clinic appointment slot for a new patient. A physician clinic was deemed to have an available appointment slot if there were enough 15-minute time units available for a new patient based on the physician's preferences (e.g. if 45 minutes were required for a new patient, then three 15-minute time units were required for a new patient appointment slot to be available, whereas if 30 minutes were required then only two 15-minute time units were needed). However, the respirologist process had one reserved appointment slot for urgent patients each week. Although only urgent patients could be scheduled into this appointment slot, the determination of the next available slot for a new patient did not exclude this urgent appointment slot. Thus, in the base case scenario, the respirologist process would have appeared to have the next available slot even if the patient was not urgent and was thus unable to use the slot. The result of this model simplification was that the respirologist queue would have been overestimated since some of the patients in this queue should have been directed to other physicians. Additionally, the time to initial assessment and time to treatment initiation would have been overestimated in all scenarios except the NoTriage scenario. In the latter configuration, the removal of both the prioritization by urgency rating and the

reserved urgent slot would have eliminated this discrepancy in appointment slot availability and distributed patients more evenly.

Of note, the effect on the time to initial physician assessment for urgent patients should not have been overestimated to the same degree, since these patients could have used the reserved slots. Moreover, if the availability of these reserved slots decreased as they were used by urgent patients, the model would direct urgent patients to the next available physician group as occurs at the SC. However, if non-urgent new patients were inappropriately assigned to the respirologist group, they would have been scheduled into unreserved appointment slots. Consequently, these unreserved slots would have been less available for urgent patients, resulting in an overestimate of $T_{Initial}$ for urgent patients. The decision to include the urgent appointment slots in the determination of the next available physician group was made in order to minimize the effects on access for urgent patients. This modeling decision likely came at the expense of overestimates of $T_{Initial}$ and T_{Treat}, and could explain part of the discrepancy between dataset outcomes and model results Thus, both the improvements for all patients and the apparent lack of a difference for urgent patients in the NoTriage configuration must be interpreted in this context. In future studies, the next available physician for urgent and non-urgent patients could be modeled separately to more accurately represent the SC.

Elimination of Alternate Care Provider Clinic (NoCPAP)

Removing the CPAP clinic had a marked detrimental effect on access, increasing the mean time to initial assessment by 288 days and the mean time to treatment initiation by

414 days. The time to treatment initiation was found to deteriorate over time, suggesting that this adverse effect would be amplified as the system became more congested. Furthermore, the significantly poorer access led to a lower adherence to CTS guidelines. Finally, the time to first PSG (T_{PSG}) was significantly lower due to a decrease in the demand for this test. The queue lengths for the respirologist process increased dramatically in the NoCPAP scenario, suggesting that worsening congestion at this bottleneck contributed to patients arriving at the PSG process less frequently. Subgroup analysis revealed similar performance to the overall results.

Simulation analysis with an increased arrival rate demonstrated even poorer performance with respect to T_{Treat} in the last month, and greater improvements in the time to first PSG. The rate of increase in the time to treatment over the simulation period was no different compared to the base case. This was an unexpected result given the marked increases in predicted utilization that were calculated from the input data. However, since the difference between $T_{Initial}$ values for the BaseCase and NoCPAP configurations were similar under baseline and increased demand conditions, the greater reduction in T_{PSG} observed in the NoCPAP scenario with increased demand may have offset the increases in T_{Treat} as the simulation progressed.

The added delays observed in the NoCPAP scenario may be underestimated due to the increased congestion in the model. The number of patients reaching treatment initiation and initial physician assessment was lower in this configuration, suggesting that many patients who would have reached outcome visits in the base case configuration were

waiting in queues at the end of the NoCPAP simulations. The increase in the total number of patients in queue at the end of the simulation runs provides further support for this conclusion. The result of this data censoring was that model performance was likely overestimated. The deterioration in outcomes with the NoCPAP scenario would likely have been greater if the outcomes were measured for the same number of patients. Data censoring could be avoided in future studies by investigating the time required for a specified number of patients to initiate treatment, or by requiring a certain number of patients to initiate treatment before a simulation run would terminate. Finally, the adverse effect of eliminating the CPAP clinic was likely further underestimated due to the underrepresentation of CPAP visits in the dataset (28% vs. 35%).

The use of alternate care providers delivering care for SDB has been suggested in the literature. Antic et al. randomized 195 patients with moderate to severe obstructive sleep apnea (OSA) to either a nurse-led pathway with ambulatory testing or the traditional physician-led pathway involving PSG (27). After three months of therapy, there was no difference in adherence to therapy, functional outcomes, daytime sleepiness, health-related quality of life, or patient satisfaction. Additionally, this study reported an economic benefit based on the use of ambulatory testing and lower cost healthcare providers. In addition to the clinical non-inferiority of alternate care provider pathways for OSA that was demonstrated by Antic, the current study highlighted the importance of alternate care providers from a patient flow perspective.

The fact that the detrimental effects of removing the CPAP clinic were simply due to a reduction in available provider capacity must be acknowledged. The CPAP clinic has the capacity to provide over 90 hours of patient care to patients with SDB each week. However, due to other clinical and professional commitments, most physicians at the SC conduct at most two half-day clinics (i.e. six hours) per week. Thus, the recruitment of up to 15 physicians would be required to make up for the absence of less than three full-time equivalent (FTE) respiratory therapists (RT). Moreover, the remuneration for physician services is greater than for RT services, suggesting that a disease-focused alternate care provider clinic is also cost-effective.

Addition of Physician Capacity (AddMD)

Based on queue lengths for physician appointments, the addition of one weekly respirologist clinic improved the mean times to initial assessment and to treatment initiation by 81 and 72 days, respectively. Furthermore, a 37% average increase was seen in the percentage of patients meeting CTS guidelines, with a 99% upper confidence limit for guideline adherence of 95%. Thus, a significant improvement in access was observed with the addition of physician resources. The mean time to first PSG increased by 63 days, reflecting the added congestion at the PSG process due to increased flow through the first physician visit. Similar to the other scenarios, this result exposed the PSG process as a second bottleneck when constraints on physician visits were relieved.

Subgroup analysis revealed similar results, including greater improvements in access to assessment and treatment for urgent patients. The addition of physician capacity had no

effect on the time to first PSG for patients for whom an urgent PSG was requested. Since these patients were of highest priority in the queue for PSG, this outcome would only have been expected to worsen if the demand for urgent PSGs increased through marked increases in patient flow or a change in the urgency mix of PSG requests. The increase in physician capacity did not result in such a large improvement in patient flow, and the case mix was assumed to be constant over the course of the simulation. Although model performance was poorer overall in the increased demand case, the improvements with the addition of physician capacity were similar.

The addition of capacity is often proposed as an initial strategy to mitigate queue formation. However, queues in healthcare systems commonly form due to inefficient resource utilization rather than an inadequate supply (87). Additionally, capacity may be added to non-bottleneck processes, resulting in further congestion at constrained processes (3) and no improvement in system performance (88).

Although beneficial results were seen with added physician capacity, the above critique of capacity expansion to address queue lengths warrants further discussion of the decision to test this scenario in the current study. First, meetings with stakeholders during the process description phase of the study revealed that queues were increasing over time, and that physician availability was the primary bottleneck. Second, preliminary spreadsheet analysis revealed utilization estimates significantly greater than one for two physician groups at the SC. Both of these findings pointed to inadequate capacity to meet demand. Finally, input from the sleep expert panel (SEP) revealed that physician

recruitment was a realistic system modification, justifying its inclusion as an alternative model configuration.

While the addition of resource capacity to unconstrained areas may worsen system performance, operations research (OR) techniques can be used to identify specific areas of constraint and to quantify the resource needs to overcome this constraint. Elkhuizen et al. used a simple queueing model to quantify demand and capacity in an urgent neurology clinic (64). Based on this analysis, a 60% increase in physician capacity was deemed necessary to meet performance targets. To explore the effects of this capacity increase on the system over time, and to include 95th percentile estimates for access to assessment, a DES model was used. The DES model demonstrated that the calculated resource estimates from the queueing model would be expected to improve access to the clinic.

Optimization of physician resources was not an objective of the current study. Thus, estimates of the necessary resource requirements to improve system delays were not calculated. However, spreadsheet calculations and simulated queue lengths were used to identify constrained processes. Based on these calculations, an informed decision to expand the respirologist clinic capacity was made.

Addition of Respiratory Therapist Capacity (AddRT)

The addition of 0.5 FTE RT capacity to the CPAP clinic was recommended as a possible system addition by Alberta Health Services (AHS) administrators. However, the performance of the AddRT model configuration was not different from baseline with

respect to any of the study outcomes, overall or in the subgroup analysis. Since the CPAP clinic was not a bottleneck in the model, it is not surprising that adding resource capacity to this process would not change model performance significantly. Furthermore, the input dataset for the current DES model included relatively fewer CPAP clinic visits than occurred at the SC from 2008 to 2010. This underrepresentation of CPAP clinic demand likely resulted in improved performance of the CPAP clinic within the model, thus reducing the benefit of adding an RT.

Simulation analysis with an increase in demand revealed a greater increase in T_{Treat} over time with the addition of an RT. Since the time to initiation of treatment in the last month was similar for the BaseCase and AddRT scenarios with increased arrivals, this result suggests that a beneficial effect on T_{Treat} may have been present earlier in the simulation. It is possible that the extra RT capacity did have a positive impact on model performance, but that this effect was overcome by system congestion due to higher demand.

The addition of RT capacity may be justified by other model performance measures. Specifically, predicted RT utilization from the input dataset was 0.91 under the base case scenario, and decreased to 0.76 with the addition of RT capacity. Moreover, both of these utilization predictions may have been underestimated due to the relative underrepresentation of CPAP clinic demand in the dataset. Higher levels of resource utilization are associated with more system congestion and a greater sensitivity to variation (see *Queueing Theory and DES* in Chapter 3). The optimal utilization threshold

for healthcare providers is not clear and depends on system characteristics and performance targets (89). However, utilization levels above 80% are considered to significantly increase the impact of variation (2). Furthermore, Elkhuizen's study demonstrated that 86% utilization was adequate to achieve 95th percentile targets for access to a gynecology clinic, while 94% utilization at a neurology clinic was not (64).

The tradeoffs between increased utilization (i.e. by decreasing provider idle time) and increased waiting times due to congestion have been explored in healthcare scheduling systems (42,46,47). These studies are not directly applicable to the current study, which did not measure waiting times in a given day. However, another indicator of system congestion is the amount of overtime work that could result from process variation in the setting of high CPAP clinic utilization levels. Discussion with the CPAP clinic RTs confirmed that overtime work was commonplace. The SC manager also identified problems with low morale related to this workload, providing another justification for the addition of extra RT capacity.

Addition of Physician and RT Capacity (AddMD_RT)

The addition of both RT and respirologist availability improved performance to a similar degree as the AddMD scenario. Subgroup analysis and simulation runs under increased demand conditions similarly showed better model performance over baseline, but the improvements were similar in magnitude to the addition of a weekly physician clinic in isolation.

Additional Insights from Data Analysis

The preliminary data analysis raised some important system issues about the SC. These insights could be helpful to SC decision-makers and AHS administrators for capacity planning, and highlight areas for future study. First, the utilization estimates for PSG, respirologists and physicians seeing only OSA patients were greater than one, suggesting that these processes were inadequately resourced to meet the weekly patient demand. Additionally, the estimated utilization for the ambulatory test (SSAT), CPAP clinic and psychologist processes approached one. As discussed above (see *Addition of Respiratory Therapist Capacity* above), average utilization levels as high as these make a system highly susceptible to the effects of variation. Thus, this preliminary analysis supported the assertion made by SC providers that resources were inadequate to serve the current patient demand.

The removal of the CPAP clinic increased the predicted utilization for almost all providers. This result is not surprising, as CPAP clinic visits in the dataset were converted to visits to the provider the patient last saw. Thus, demand estimates for most providers increased. The only exception was the neurologist, since the patients seen by the neurologist in the dataset did not have any CPAP clinic visits. As expected, utilization estimates for the respirologist and CPAP clinic RT decreased with the addition of each of these resources. Since the addition of resources only increased capacity estimates, the predicted utilization for other resources did not change when respirologist or RT capacity was increased. Similarly, predicted utilization for the respirologist and

RT did not increase in an additive way when the AddMD_RT scenario was applied to the utilization calculations.

The estimated utilization for the physicians seeing only OSA patients was very high (1.59), suggesting profoundly inadequate resources. This result should be interpreted with caution, due to the nature of the historical data used for the utilization calculations. The visit data used to estimate demand was the dataset of 150 referrals from 2007, whereas the capacity estimates were based on the average weekly number of clinics from the 2008-10 data. From 2008 to 2010, the frequency of clinics conducted by these physicians decreased significantly due to physician attrition at the SC. Thus, due to temporal differences in the data used to estimate demand and capacity, the calculated utilization likely overestimates the true utilization of this physician group. Conversely, the frequency of clinics conducted by the neurologist increased slightly from 2008 to 2010, resulting in a probable underestimate of neurologist utilization. Since neither of these resources was the model bottleneck based on final queue lengths, it was not expected that these discrepancies would have affected model performance with respect to the study outcomes. Moreover, due to these limitations in predicting resource utilization, queue lengths were used to identify the most constrained physician group for the AddMD scenario.

Second, knowledge of the clinical pathways taken by patients at the SC complements the utilization predictions. As is seen in Figure 1, the majority of patients are assessed by physicians, directly after referral or after SSAT testing. It is thus not surprising that

utilization estimates were greatest for some physician groups, and that one of these groups (respirologists) was the main source of congestion in the model. Based on this information, model improvements that increased physician resources or improved the efficiency of physician visits were justified. Furthermore, many patients who are referred to the SC are eventually assessed by the CPAP clinic therapists, providing further rationale for improving care delivery at this process. In contrast, a minority of patients are assessed by the psychologist. Therefore, while the psychologist provides assessment and treatment for an important group of sleep disorders (e.g. insomnia), this clinical pathway is less important from the perspective of improving access for the greatest number of patients. Finally, although a minority of patients undergoes PSG testing, the high utilization estimates suggest that the demand is greater than can be managed by the current capacity. Given that PSG testing is the gold standard diagnostic test for sleep disorders, this preliminary result supports further attention to PSG resource capacity. While the current study did not explore the effects of changes in PSG capacity, this is an important area for future study.

Third, examination of all 2007 referrals revealed that 30% of the patients did not undergo assessment or testing at the SC. This finding was reviewed with SC administrators and was found to be a consistent observation. The high dropout rate could be related to patients who choose not to enter the queue (balk) or leave the queue (renege) in favour of a private care pathway. The choice to balk or renege in this case is usually driven by the long delays for assessment at the SC; thus, it is possible that additional demand could manifest at the SC if the delays were reduced. Since many sleep disorders have

nonspecific complaints (e.g. fatigue, concentration difficulties), patients might also balk if they do not perceive the need for assessment by a sleep provider. Improving the efficiency of the SC would not attract these patients to any greater degree, although many of them may not have a sleep disorder. All referrals require initial processing by SC staff. Thus, although clerical resources were not modeled explicitly in the current study, reducing the dropout rate could improve the amount of unnecessary work for staff at the referral and triage process.

A fourth observation regarding the system was the high appointment cancellation rate, which was over 10% for all processes and ranged from 25-40% for all physicians and the psychologist. Missed appointments were much less common but still occurred for up to 8% of visits. The high cancellation and missed appointment rates occurred despite reminder telephone calls that occur before a scheduled appointment. The likelihood of cancellations and missed appointments has been linked to a number of factors, including the delay from referral to appointment date (90). In a study of a psychiatric outpatient clinic with a mean delay of 47 days from referral to initial assessment, Gallucci *et al* demonstrated a 12% increased odds of cancellation or missed appointment per day of delay (91). Given the significant demand backlog at the SC, it is possible that delays from the referral or appointment request date to the actual appointment date contribute significantly to the cancellation rate.

There are many potential consequences of a high cancellation rate at the SC. First, although demand is high overall, interviews with SC clerical staff revealed that cancelled

slots are often difficult to fill due to patient preference for a specific appointment date or the inability to attend a clinic visit on short notice. Current research supports this observation; a study of a family medicine clinic revealed that 39% of cancelled or missed appointments could not be filled, despite a significant demand from unscheduled 'walk-in' patients (56). Thus, considerable underutilization of bottleneck resources likely results from frequently cancelled appointments. Furthermore, the rescheduling of unpredictable and frequent cancellations may cause demand variation, further worsening inefficiency and delays. Finally, processing and rescheduling cancellations, which includes preparing discharge letters for patients with multiple cancelled or missed appointments, add a significant workload to the SC clerical staff. In the current study, the amount of wasted resource capacity for SC processes or clerical work was not modeled, but could be considered in future studies to further quantify the adverse effects of cancelled or missed appointments.

With respect to model outcomes, the SEP supported the choice of the time to initiation of treatment as the key performance measure for this study. Examination of the input dataset revealed that 35% of these patients did not achieve the pre-specified definition of treatment initiation, which included an initial visit to the CPAP clinic or SC psychologist, or a second physician visit. The reasons for many patients not meeting one of these criteria could not be ascertained from analysis of the data. However, possible explanations include an initial physician assessment that revealed no sleep disorder, a less severe sleep disorder (e.g. chronic sleep deprivation) that was treated with clinical advice at a single visit, or failure of the patient to follow-up. Additionally, some patients are

followed by non-sleep respirologists and are referred for PSG only; these patients may undergo a single assessment by a sleep physician, but are followed by the referring physician. Thus, while the use of an outcome that only affected 65% of the study cohort could represent a biased measure of model performance, it is likely that this 65% represent the patients with the greatest need for services at the SC. The SEP still thought that the time to treatment initiation was the most important outcome measure, but agreed that secondary outcomes such as the time to initial physician assessment and time to initial PSG were important to measure access for patients who did not meet the definition for treatment initiation. Importantly, 93% of patients in the input dataset met at least one of the study outcomes.

Additional Insights from DES Model

Comparisons of the dataset and base case model outputs revealed discrepancies for some performance measures. In particular, the time to treatment initiation and time to initial physician visit were overestimated for urgent patients in the model. These discrepancies likely relate to issues with model coding that would have affected the prioritization of urgent patients. First, the oversimplified determination of the next available physician group inappropriately loaded the respirologists with non-urgent patients (see *Elimination of Urgency Rating* above). This added load resulted in fewer available appointment slots for urgent patients. Since many urgent patients have respiratory disease or complicated sleep-disordered breathing, they are often only able to see a respirologist. Thus the limited access for urgent patients would have been made worse by the loading of the

physician group whose services they were most likely to need. Second, although the initial description of the SC suggested that urgent referrals were always placed in queue with the highest priority (see Appendix A), the queue policy reported by the booking clerk responsible for scheduling these patients effectively prioritized patients based primarily on referral date and secondarily on urgency. The model was coded using the latter configuration, thus disadvantaging urgent patients in queue relative to the queueing policy suggested by the process description. Further clarification would be required to delineate the true prioritization policy. Third, because linked appointment scheduling was not modeled, patients who required PSG before initiating treatment would have been scheduled for a follow-up physician visit after the PSG was completed rather than when it was requested. Thus, any potential reduction in delays from linked scheduling would have been lost, resulting in overestimates of T_{Treat}. This added delay from the absence of linked scheduling would differentially affect urgent patients, since the dataset revealed that most (82%) of them underwent PSG before initiating treatment. Finally, as discussed above, changes in resource availability from 2007 to 2010 may have affected the processing of urgent patients, such that delays would be longer under current system parameters. Importantly, sample sizes for these subgroups were small in the dataset. Although a representative sample of patients was selected from the 2007 referral list to ensure that all important visit trajectories were captured, it is possible that some of the visit delays may not accurately reflect the actual delays at the SC. Further model adjustments and prospective validation of outputs could be used in the future to explore these discrepancies further.

Similar overestimates were noted for the time to initial PSG for all patients and for urgent patients. For these outcomes, it is important to recognize that the model representation of this outcome included a mandatory 30 day delay for technologist scoring and physician interpretation of the PSG. The estimate from the dataset did not include this additional delay, resulting in a model output that was systematically biased by 30 days. Moreover, a simplifying assumption in the model was that no urgent slots would be reserved in the PSG schedule, contrary to the actual system. This assumption was deemed acceptable by the SEP, since with the 30-day PSG scheduling horizon and the prioritization of patients requiring urgent PSGs, urgent PSG requisitions would always have priority access to slots 31 days in the future. Thus, although urgent slots were not reserved, the short scheduling horizon and queue policy would result in a smaller discrepancy between the model results and the actual system. It was acknowledged that the estimates for T_{PSG} might be overestimated on this basis. If these added delays are considered in the comparison of the dataset to the model outputs, the discrepancies for T_{PSG} are much lower and could be explained by the variability in the dataset values. Additionally, the discrepancy in T_{Treat} for urgent patients may have been influenced by the difference in T_{PSG}, since the majority of urgent patients underwent PSG prior to treatment initiation.

Another discrepancy between the DES model and the dataset relates to the utilization predictions for a steady-state scenario with reduced demand. While utilization estimates were similar for resources with fixed capacity (SSAT, PSG, CPAP clinic) or with very low clinic cancellation rates (psychologist), further exploration revealed an underestimation of clinic cancellation rates for some physician groups. Future studies

should use a model in which these cancellation rates are more accurately represented, as the resulting overestimated resource capacities likely artificially improved model performance. It appears from this post-hoc model reconfiguration that other aspects of the model that could affect resource capacity or demand are accurately coded, since the utilization estimates following an upward adjustment of the clinic cancellation probabilities were similar in the dataset and model. Of note, the "Professional Consult" workload was not adjusted despite a reduction in demand in this analysis. Thus, while the CPAP clinic appeared to be the process with the highest utilization, it is probable that the "Professional Consult" workload would decrease proportionally to the reduction in patient arrivals.

The suggestion from the model results that urgent patients take longer to initiate treatment than non-urgent patients should be interpreted with caution. First, as discussed above, model coding contributed to unexpectedly worse results for urgent patients. Further verification and validation is required to resolve these issues. Notwithstanding potential improvements in the handling of urgent patients from corrections to the model, a discussion of the clinical context of urgent patients is also important to understand this finding. Specifically, the visit trajectory of urgent patients is usually different from non-urgent patients. Commonly, the visit trajectory of non-urgent patients is characterized by a single-physician visit followed by a CPAP clinic or psychologist visit, or two consecutive physician visits without any intervening tests. In contrast, urgent patients often undergo PSG testing before returning to a provider to initiate treatment. Since PSG testing is a relatively constrained process at the SC, the delays are longer for patients

whose path to treatment initiation involves PSG compared to those who do not require PSG. In the input patient dataset used in the current study, 82% of urgent patients underwent PSG, compared to 35% overall. Thus, the longer time to treatment initiation in the model is not unexpected. Of note, the time to initial physician assessment was lower for urgent patients compared to the entire cohort of patients, suggesting that some appropriate prioritization by urgency was occurring. In future studies, a valuable comparison between alternatives would be T_{Treat} for urgent patients requiring PSG compared to non-urgent patients requiring PSG, to demonstrate more accurately how the delays may differ depending on urgency rating. If the results of such a comparison in a corrected model did not reveal a benefit of prioritization by urgency for urgent patients, then it would be reasonable to question the utility of this prioritization strategy.

The improvement of some model outcomes was associated with a deterioration in others. Specifically, T_{PSG} was inversely related to both T_{Treat} and $T_{Initial}$. The notion of tradeoffs between performance measures has been discussed in previous studies of outpatient clinics (46,48). Plotting model outputs against each other enables an assessment of the relative performance effects of model configurations. Additionally, the 'best' scenario from the perspective of the plotted outputs can be determined as that which simultaneously improves both measures. In the current study, tradeoff curves supported the observation that improving access to initial assessment or treatment by eliminating prioritization by urgency or by adding physician capacity would worsen access to PSG (see Figures 7 & 8). Conversely, the removal of the CPAP clinic improved access to PSG while adversely affecting the other measures. This result exposed the shift of the

bottleneck as access to physician appointments was improved. The base case scenario minimized T_{Treat} or $T_{Initial}$ and T_{PSG}, suggesting it was the 'best' configuration with respect to these outcomes. However, it is important to note that only a minority (35%) of referred patients underwent PSG, whereas 65% initiated treatment and 80% had at least one physician visit. The tradeoff curves do not capture the relative weighting of these outcome measures, which would certainly affect the choice of alternative configuration given these results. The current study did not model increases in PSG capacity, but the constraint on the model by the PSG process under alternative scenarios makes this an important consideration for future research.

Another insight supported by the tradeoff curve in Figure 9 was that the improvements in access to treatment were not associated with deteriorations in access to initial assessment. It is possible that queueing policies or clinical pathways could improve one outcome at the expense of another, as was observed for T_{PSG} with improvements in access to provider visits. For example, although both T_{Treat} and $T_{Initial}$ are related to provider visits, a strategy that prioritized new patients in physician queues could worsen the time to treatment initiation while improving the time to initial physician visit. In future studies, it would be important to consider this potential tradeoff when testing other alternative scenarios.

Although the current study did not analyze the time to different physician visits as separate outcomes, the queue lengths at the end of the simulation demonstrate some interesting differences in the response to alternative scenarios. Specifically,

improvements in the respirologist queue were associated with longer queues for the neurologist and general internist in the NoTriage scenario. This finding probably relates to the physician assignment for newly referred patients in the DES model. As discussed above (see *Elimination of Urgency Rating* above), the inclusion of reserved urgent slots in the determination of the next available physician resulted in the inappropriate assignment of non-urgent patients to the respirologist when another physician group had the next available appointment slot, . As a result, queues for the respirologist were likely overestimated and queues for the other physicians were likely underestimated. Interestingly, the queue length for physicians seeing only OSA patients did not increase, as was seen for the other physician groups when this physician assignment error was eliminated in the NoTriage scenario. The explanation for this finding likely relates to the fact that the neurologist and general internist see a broader range of patients than the OSA only physicians. Thus, more patients that would otherwise have been assigned to these physician groups were inappropriately assigned to the respirologist group. When the NoTriage scenario was implemented, a larger load was placed on the neurologist and general internist compared to the OSA only physicians, leading to the growth in their queue lengths. Since patients with OSA can be seen by any physician at the SC, any increase in demand on the OSA only physicians in the NoTriage scenario would have been distributed among other physician groups as well.

Some of the unexpected changes in process queue lengths might be explained by congestion at the process immediately preceding the process in question. For example, if significant congestion was present at the PSG process due to inadequate PSG capacity,

then the queue for the respirologist process might be smaller than expected since many patients would be waiting for PSG before entering the respirologist queue. Since utilization estimates were greater than or approached one for a number of processes, it is likely that queues at the bottleneck processes were underestimated. Further exploration of specific areas of congestion within the model could clarify the distribution of patients in queues for highly congested resources.

For the NoCPAP scenario, the increase in queues was due to increased visit demand from visits that were CPAP clinic visits in the base case configuration. This finding is consistent with the increased times to initial physician assessment and treatment initiation observed in simulation runs of this scenario. Furthermore, the deterioration in model performance with this configuration was likely underestimated, since the throughput for initial assessment and treatment initiation were decreased. Thus, many patients, who would have had much longer delays, were not included in the calculation of these outcomes. An alternative modeling approach to mitigate the effect of data censoring would have been to calculate model performance measures for a similar number of patients in each configuration. This strategy would have involved either identifying a specific subset of patients for whom performance measures would be captured, or changing model termination parameters to ensure that a pre-specified number of patients reached the desired outcome visits. Furthermore, measures of the number of patients meeting outcomes or the total number of patients in the model could be used to support conclusions regarding model performance and model congestion.

Queue lengths grew as expected in the increased demand case, with two notable exceptions. For the CPAP clinic, an infinite scheduling horizon is used, whereby there is no limit to the scheduling of appointments in the future. Thus, increased demand would not manifest as an increased queue length, since patients could simply be scheduled further into the future. Interestingly, the psychologist queue also did not grow with increased demand, despite a finite scheduling horizon. Review of the input data revealed that the psychologist conducted over 95% of possible clinics over the period from which historical data was obtained. In contrast, the physician groups (respirologist, neurologist, OSA only physician and general internist) only conducted between 42% and 91% of possible clinics. Thus, the significant capacity variation from high clinic cancellation rates likely contributed to the increased queues at the end of simulation for the increased demand case.

It is important to acknowledge that the queue lengths at the end of simulation did not represent all patients in the system. The queue lengths used in the current study represented the number of patients waiting to be scheduled, but did not include those who had been scheduled and were waiting for their appointment date. These patients represent a load on the system, and only differ from the patients in queue by the fact that a scheduling horizon permits some to be scheduled while others must wait. A future consideration to estimate congestion at a particular process would be to measure all patients waiting for a visit, regardless of whether an appointment date had been assigned. This count of patients 'in progress' would enable a more accurate assessment of constrained areas of the model, and would better inform interventions to improve access.

Despite modifications that reduced waiting times for assessment, advanced diagnostic testing and treatment initiation, none of the model perturbations changed the unstable nature of the model. T_{Treat} increased over the three year simulation period in all scenarios, suggesting that the SC would not represent a steady-state system even if any of the proposed alternatives were implemented. Given the high demand and multiple processes with high predicted utilizations, this finding was not unexpected. Capacity increases would need to be of greater magnitude in order to mitigate the rising queue lengths over time.

Limitations

There are a number of important limitations to the current study that must be acknowledged. First, operational validation using prospective system data was not performed, due to the unavailability of system data for comparison. Thus, it is possible that the model outputs do not adequately approximate the true performance of the system. However, some model results were reviewed with subject matter experts and determined to be reasonably similar to perceived actual system performance. The modifications made to the database will provide this data for critical comparisons to model outputs in the future.

A second threat to model validity relates to the use of input data from 2007 referrals and 2008-10 system data. It is possible that patient arrival patterns, resource availability or queueing policies could have changed between the collection of this data and the present. As a result, data collected for the purposes of model construction may not have

accurately represented the current system, making future comparisons to system data difficult. The decision to use older data was made to ensure that visit histories would be available for the patients in the dataset. When operational validation is performed, these differences will require consideration.

The modeling of each alternative configuration as a separate model (see *Model Perturbations* in Chapter 4) presents a second limitation for the analysis and interpretation of study results. With this approach, comparisons of model outputs in the last simulated month examined the potential differences if the system had been designed differently, rather than if the alternative scenarios were implemented in an existing system. Furthermore, while the change in T_{Treat} over the simulation period measured relative model performance over time, this outcome did not address the possibility that the loading of a model representing an alternative scenario was incomplete when data collection started. Another approach warranting consideration in future studies would be to design a single model in which an alternative configuration would be implemented after initialization. Although such a strategy could add significant technical considerations for model construction, comparisons of absolute measures such as the ones used in the current study would depend on model performance rather than initialization. Additionally, rather than the current study, in which model changes were implemented at inception, a single model that underwent a specific change after a period of time would be more reflective of the way in which system changes at the SC would be likely to occur.

The use of multiple statistical comparisons for secondary outcomes and subgroup analysis is a third limitation. Although a Bonferroni correction was performed based on the number of comparisons for the primary outcome, the corrected alpha of 0.01 did not account for these further statistical comparisons. Thus, the simulation outputs could reveal model performance changes that are due to chance alone. While there is a greater risk of type I error, the model perturbations often showed consistent findings across multiple performance measures, suggesting that the effects were real.

A fourth limitation is the generalizability of the model and the study results. DES models are designed to answer questions about a particular system, and are conceptualized with assumptions and approximations that are specific to that system. Consequently, it is difficult to apply them to other systems. The primary purpose of the current study was to understand and improve operational aspects of the SC. However, examination of alternative scenarios within the model led to important conclusions that could be applied to other sleep centres. A primary example is the positive contribution that alternate care provider clinics had on access to assessment and treatment for patients with SDB. Furthermore, the increased demand case may provide some suggestion of these improvements on sleep centres with different demand patterns.

In order to generalize the findings of the current study, the environmental context must be recognized. The SC is a single publicly funded centre amidst a number of private sleep diagnostic and treatment companies in Calgary; currently, many patients with uncomplicated obstructive sleep apnea are diagnosed and treated at one of these centres,

and are thus never referred for further assessment at the SC. As the capacity of private companies increases, the number, composition and complexity of referrals to the SC could change. Patients that bypass the SC were not captured in the model, but the increased demand case was designed to explore the possibility of additional referrals from the private sector. Future research could address this concern by expanding the current model to capture the private sector.

Another generalizable aspect of the current project is the application of OR and DES to sleep medicine. Studies related to access to care for sleep disorders have emphasized clinical rather than operational outcomes. Furthermore, the only work examining operational barriers to access was a complete system redesign that did not delineate the individual contributions of the system improvements that were implemented (81). In particular, DES modeling would allow for the operational analysis of different sleep centres, which have different demand patterns, service processes and queueing disciplines. The important considerations to perform a similar analysis using OR and DES at another sleep centre are discussed below (see *Considerations for Study Replication* below).

Considerations for Study Replication

The current study involved the operational analysis of the SC using analysis of historical data and DES modeling. The study revealed a number of insights specific to the SC that, while potentially applicable more broadly, do not replace system-specific analysis at other sleep centres. Based on existing frameworks for approaching OR problems using

simulation (71,82), this section highlights the important considerations for such an analysis. First, a clear and well formulated purpose is mandatory for guiding further analysis. There is significant variability in the models of care for sleep disorders (See *Service Delivery for Sleep Disorders* in Chapter 2). Thus, emphasis may be placed on different aspects of the system depending on the unique access issues for that system (e.g. waiting time for PSG, number of patients initiating CPAP for OSA annually).

The availability of reliable operational data to answer the problem of interest is another important requirement. This data may help to expose or refine the problem by identifying bottlenecks and delays, and facilitates a process description. Data availability also helps to determine what type of analysis is best suited to the problem (82), and will influence the validity and credibility of the project (71). Moreover, previous OR studies in healthcare have demonstrated that the timeline for study completion is affected by the availability of data (59,92). In the current study, significant database modifications were required to collect the appropriate information, leading to delays in the completion of the project and validity concerns as outlined above (see *Limitations* above). These challenges may not exist at a sleep centre with a data collection infrastructure that includes both time stamp data and clinical variables.

A description of the system of interest is a critical part of an operational analysis. While there are fundamental differences between the SC and other sleep centres, such as the use of SSAT testing and the immersion in a private sector for sleep care, the process description of another centre would highlight other subtle yet important differences.

Examples include the queueing policies for provider visits and diagnostic tests, triage criteria or demand patterns. In addition to observing the system and interviewing providers and managers, system data would be paramount for this purpose.

Essential to the above steps, and to ensure model validity and credibility, is the regular involvement of system stakeholders. In the current study, the SEP provided useful insights into the model inputs, desired performance measures, and the function of the SC itself. Additionally, AHS administrators responsible for SC policies were available for consultation regarding realistic model perturbations. In contrast, some sleep centres are one of many administered by a single administrative agency (e.g. Veterans Health Administration) (13). Replicating the current study for such centres may require modeling of multiple sites or further generalizability considerations than were made in the current study. Moreover, the analysis of systems where private and public sleep centres offer the same services may require more detailed modeling of balking and reneging from queues due to delays. Stakeholder input would be required to highlight these and other additional considerations at other sleep centres.

Future Research

The results of the current study highlight a number of areas for future research. The DES model was designed to address the issue of access to treatment for sleep disorders. However, the model was flexibly constructed to allow for further related analyses to be performed. Examples include modification of reserved slots for new and urgent patients, or changes to the PSG queueing policy to incorporate likely sleep diagnosis rather than

urgency alone. The model was parameterized where possible to allow for sensitivity analyses with changes to cancellation rates or clinic schedules.

A second area for future work is the implementation of study results. The purpose of DES models is to provide insight into system performance under a variety of configurations. However, due to poor acceptance of simulation methodology, the implementation of simulation results has lagged far behind other disciplines, such as the military or manufacturing (76,93). The current study highlights alternative system configurations that could improve operational performance if implemented. Although decision makers at the SC were accepting of the DES model's outcomes, demonstration of the model's results in the actual system will be important for construct validation of DES in healthcare.

In the current study, it was assumed that a patient's actual visit trajectory was based on best practice as determined by the sleep provider and patient. Optimal clinical pathways for patients with different sleep disorders or comorbidities have not been identified. Determination of these pathways could reduce service variation, thus improving the operational efficiency of the SC. Furthermore, exploration of the number of CPAP clinic visits after which incremental benefit is minimal could drive policy around CPAP clinic utilization by individual patients. Yet another dimension to the identification of best clinical pathways would involve incorporation of the private sector into future process descriptions and simulation studies.

The referral and triage process is a major determinant of provider selection and flow pathways for newly referred patients. However, this process and the criteria used to determine urgency are unvalidated. While the urgency rating process appeared to worsen model performance, it may also be true that the prioritization tool is based on incorrect criteria, thus leading to inappropriate queueing of patients. Future research should explore the important aspects of the triage system and repeat simulation studies could investigate the effects of alternative triage systems on model performance.

Conclusion

Despite access limitations for sleep care around the world, there are no published studies of operational analyses of existing sleep centres. The current study explored the barriers to access at a publicly funded, academic sleep centre. Using OR applications such as queueing theory and simulation, insights into the performance of the SC were obtained. Key findings of the current study to report to SC administrators include:

- The apparent resource inadequacies for physician clinics and PSG testing
- The importance of the alternate care provider clinic to ensure access to the SC
- The 'safer' RT utilization levels afforded by RT capacity increases
- The need to explore the current triage process and triage criteria in more detail

Importantly, this study highlights the role of OR and DES for examining the performance of complex medical systems. The future implementation of these study results and the

analysis of other operational questions at the SC will enhance the validity of OR methods as tools to improve the efficiency of healthcare delivery.

Table 1. Clinical Characteristics of Input Dataset Patients

Characteristic	2007 Dataset	%
Referral Status		
Referred	115	77
Not Referred	35	23
Total Patients	150	100
Urgency		
Primary Urgent	11	10
Secondary Urgent	27	23
Semi Urgent	27	23
Normal	50	43
Total with Urgency	115	100
Occupational Risk	9	8
Epworth Sleepiness Scale	11	---
Patient Type		
Any (OSA)	63	55
Insomnia	9	8
RLS, PLMD, Narcolepsy	13	11
Respiratory	28	24
Neurologic	1	1
Chronic Fatigue	1	1
Total with Patient Type	115	100

SSAT = ambulatory sleep test; OSA = obstructive sleep apnea; RLS = restless legs syndrome; PLMS = periodic limb movement disorder

Table 2. Distribution of Patient Visits in Input Dataset and in 2008-10 Data

Visit Type	2007 Dataset		2008-10 Data		
Diagnostic Tests	**Count**	**%**	**Count**	**%**	**p value**
SSAT	130	65	4501	63	0.68
PSG	69	35	2617	37	0.68
Totals	199	100	7118	100	---
Provider Visits					
CPAP Clinic	110	28	3777	37	<0.001
Respirologist	137	35	2928	29	0.008
Neurologist	4	1	192	2	0.21
OSA only Physician	53	13	845	8	< 0.001
General Internist	43	11	1265	12	0.39
Psychologist	47	12	1261	12	0.82
Totals	394	100	10268	100	---

SSAT = ambulatory sleep test; PSG = polysomnography; CPAP = continuous positive airway pressure; OSA = obstructive sleep apnea. P values are for a two-tailed t-test.

Table 3. Cancellations and Missed Appointments from 2008-10 Data

Visit Type	% Cancelled	% Missed
SSAT	14.71	4.98
PSG	10.93	2.42
CPAP Clinic	14.82	5.86
Respirologist	33.26	7.58
Neurologist	40.11	8.13
OSA only Physician	32.80	4.52
General Internist	28.50	6.43
Psychologist	25.25	7.21

SSAT = ambulatory sleep test; PSG = polysomnography; CPAP = continuous positive airway pressure; OSA = obstructive sleep apnea. Cancelled appointments are presented as a percentage of all scheduled appointments (including cancelled and missed appointments), whereas missed visits are presented as a percentage of all available slots (including missed but not cancelled appointments).

Table 4. Performance Measures from Input Dataset

Outcome	Mean	n
T_{Treat} (days)	266 (212)	97
Urgent Patients	100 (38)	10
SDB Patients	246 (221)	68
$T_{Initial}$ (days)	222(164)	120
Urgent Patients	58 (38)	11
T_{PSG} (days)	46 (64)	52
Urgent PSG	30 (70)	21
% Meeting CTS Guidelines	61	51
High Risk Patients	7	4

T_{Treat} = time to initiation of treatment; SDB = sleep-disordered breathing; $T_{Initial}$ = time to initial physician visit; T_{PSG} = time to initial polysomnography; PSG = polysomnography; CTS = Canadian Thoracic Society; n = mean number of patients reaching outcome. Results are presented as mean (SD) for T_{Treat}, $T_{Initial}$ and T_{PSG} and related subgroups

Table 5. Predicted Resource Utilization from 2008-10 Data

Resource	BaseCase	NoTriage	NoCPAP	AddMD	AddRT	AddMD_RT
SSAT	0.93	0.93	0.93	0.93	0.93	0.93
PSG	1.14	1.14	1.14	1.14	1.14	1.14
CPAP RT	0.91	0.91	---	0.91	0.76	0.76
Respirologist	1.27	1.27	1.72	1.11	1.27	1.11
Neurologist	0.50	0.50	0.50	0.50	0.50	0.50
OSA only Physician	1.59	1.59	2.06	1.59	1.59	1.59
General Internist	0.88	0.88	1.16	0.88	0.88	0.88
Psychologist	0.96	0.96	1.01	0.96	0.96	0.96

SSAT = ambulatory sleep test; PSG = polysomnography; CPAP = continuous positive airway pressure; RT = respiratory therapist; OSA = obstructive sleep apnea.

Table 6. Simulation Results for Base Case Scenario

Outcome	Mean	99% CI	n
T_{Treat} in the last month (days)	263	(253,274)	123 (10)
Urgent Patients	397	(374,420)	11 (4)
SDB Patients	222	(213,231)	79 (9)
% Change in T_{Treat}	30	(25,35)	---
$T_{Initial}$ in the last month (days)	200	(193,207)	156 (10)
Urgent Patients	165	(156,173)	14 (4)
T_{PSG} in the last month (days)	154	(145,163)	67 (4)
Urgent PSG	59	(59,60)	29 (5)
% Meeting CTS Guidelines	56	(53,60)	71 (8)
High Risk Patients	7	(5,9)	39 (6)

T_{Treat} = time to initiation of treatment; SDB = sleep-disordered breathing; $T_{Initial}$ = time to initial physician visit; T_{PSG} = time to initial polysomnography; PSG = polysomnography; CTS = Canadian Thoracic Society; n = mean number of patients reaching outcome (SD)

Table 7. Results for Time to Initiation of Treatment in Last Month of Simulation

	Output (days)		Change (days)		n
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	263	(253,274)	---	---	123 (10)
NoTriage	220	(209,232)	-43	(-56,-30)	120 (11)
NoCPAP	677	(651,704)	414	(387,441)	92 (11)
AddMD	191	(183,200)	-72	(-84,-60)	124 (10)
AddRT	259	(248,270)	-5	(-19,10)	119 (13)
AddMD_RT	194	(185,202)	-70	(-81,-58)	118 (13)

n = mean number of patients reaching outcome (SD)

Table 8. Subgroup Analysis of Time to Initiation of Treatment in Last Month of Simulation

Urgent Patients	Output (days)		Change (days)		n
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	397	(374,420)	---	---	11 (4)
NoTriage	389	(352,425)	-8	(-47,30)	11 (4)
NoCPAP	1066	(1015,1117)	669	(610,727)	8 (3)
AddMD	245	(224,267)	-152	(-185,-119)	12 (4)
AddRT	394	(373,415)	-4	(-30,23)	10 (3)
AddMD_RT	254	(230,277)	-144	(-173,-115)	12 (4)

Patients With SDB	Output (days)		Change (days)		n
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	222	(213,231)	---	---	79 (9)
NoTriage	181	(170,192)	-41	(-55,-27)	78 (8)
NoCPAP	765	(725,804)	543	(504,582)	38 (8)
AddMD	150	(142,158)	-72	(-83,-62)	80 (9)
AddRT	224	(214,235)	2	(-11,16)	77 (11)
AddMD_RT	154	(146,163)	-68	(-79,-57)	77 (10)

SDB = sleep-disordered breathing; n = mean number of patients reaching outcome (SD)

Table 9. Results for Change in Time to Initiation of Treatment over Simulation

	Output (%)		Change (%)	
	Mean	**99% CI**	**Mean**	**99% CI**
BaseCase	30	(25,35)	---	---
NoTriage	45	(37,53)	14	(4,25)
NoCPAP	41	(35,47)	11	(2,19)
AddMD	24	(19,29)	-6	(-13,1)
AddRT	29	(24,33)	-2	(-9,6)
AddMD_RT	25	(19,30)	-6	(-14,3)

Table 10. Results for Time to Initial Physician Visit in Last Month of Simulation

	Output (days)		Change (days)		n
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	200	(193,207)	---	---	156 (10)
NoTriage	147	(139,156)	-53	(-62,-44)	160 (11)
NoCPAP	487	(477,498)	288	(275,300)	141 (10)
AddMD	119	(112,126)	-81	(-89,-72)	159 (13)
AddRT	198	(190,205)	-2	(-12,7)	159 (13)
AddMD_RT	124	(118,129)	-76	(-84,-68)	166 (12)

n = mean number of patients reaching outcome (SD)

Table 11. Subgroup Analysis of Time to Initial Physician Visit in Last Month of Simulation

Urgent Patients	Output (days)		Change (days)		n
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	165	(156,173)	---	---	14 (4)
NoTriage	151	(137,165)	-14	(-28,1)	14 (4)
NoCPAP	582	(562,601)	417	(395,439)	12 (4)
AddMD	40	(35,44)	-125	(-135,-116)	15 (4)
AddRT	161	(152,170)	-4	(-17,9)	14 (4)
AddMD_RT	39	(35,44)	-125	(-135,-116)	16 (3)

n = mean number of patients reaching outcome (SD)

Table 12. Results for Time to Initial Polysomnography in Last Month of Simulation

	Output (days)		Change (days)		N
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	154	(145,163)	---	---	67 (4)
NoTriage	188	(176,201)	35	(17,52)	66 (3)
NoCPAP	39	(38,41)	-114	(-124,-105)	62 (7)
AddMD	216	(205,228)	63	(49,77)	67 (4)
AddRT	160	(149,170)	6	(-7,20)	67 (4)
AddMD_RT	227	(215,238)	73	(59,87)	66 (4)

n = mean number of patients reaching outcome (SD)

Table 13. Subgroup Analysis of Time to Initial Polysomnography in Last Month of Simulation

Urgent PSG	Output (days)		Change (days)		N
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	59	(59,60)	---	---	29 (5)
NoTriage	59	(59,60)	0	(-1,1)	29 (6)
NoCPAP	33	(33,34)	-26	(-27,-25)	26 (5)
AddMD	59	(59,60)	0	(-1,1)	29 (5)
AddRT	59	(59,60)	0	(-1,1)	29 (5)
AddMD_RT	59	(59,60)	0	(-1,1)	28 (5)

PSG = polysomnography; n = mean number of patients reaching outcome (SD)

Table 14. Results for Percentage of SDB Patients Meeting CTS Guidelines in Last Month of Simulation

	Output (%)		Change (%)		N
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	56	(53,60)	---	---	71 (8)
NoTriage	78	(73,84)	22	(16,28)	73 (8)
NoCPAP	38	(35,40)	-19	(-24,-14)	52 (7)
AddMD	93	(92,95)	37	(33,40)	70 (8)
AddRT	56	(53,60)	0	(-5,5)	70 (9)
AddMD_RT	91	(90,93)	35	(31,39)	71 (10)

SDB = sleep-disordered breathing; CTS = Canadian Thoracic Society; n = mean number of patients reaching outcome (SD)

Table 15. Subgroup Analysis of Percentage of SDB Patients Meeting CTS Guidelines in Last Month of Simulation

High Risk CTS Patients	Output (%)		Change (%)		n
	Mean	99% CI	Mean	99% CI	
BaseCase	7	(5,9)	---	---	39 (6)
NoTriage	5	(3,7)	-1	(-4,1)	40 (6)
NoCPAP	0	(0,0)	-7	(-9,-5)	32 (6)
AddMD	5	(3,7)	-2	(-4,0)	40 (6)
AddRT	5	(4,7)	-2	(-4,1)	39 (6)
AddMD_RT	5	(3,7)	-2	(-4,0)	41 (7)

SDB = sleep-disordered breathing; CTS = Canadian Thoracic Society; n = mean number of patients reaching outcome (SD)

Table 16. Mean Process Queue Lengths at End of Simulation

Baseline Demand	BaseCase	NoTriage	NoCPAP	AddMD	AddRT	AddMD_RT
SSAT	6 (12)	7 (12)	2 (1)	12 (32)	9 (17)	10 (19)
PSG	315 (90)	443 (96)	3 (2)	543 (87)	335 (90)	572 (68)
CPAP Clinic	0 (1)	1 (1)	---	1 (1)	1 (1)	1 (1)
Respirologist	484 (157)	280 (140)	4385 (151)	5 (2)	458 (144)	5 (2)
Neurologist	13 (19)	83 (66)	70 (48)	3 (7)	18 (19)	6(8)
OSA only Physician	2 (2)	3 (2)	2 (2)	2 (2)	2 (2)	1 (2)
General Internist	3 (2)	16 (16)	12 (10)	3 (3)	3 (2)	3 (2)
Psychologist	3 (2)	3 (1)	3 (2)	2 (1)	3 (2)	3 (1)
Total	826	836	4477	571	829	601

Increased Demand	BaseCase	NoTriage	NoCPAP	AddMD	AddRT	AddMD_RT
SSAT	388 (145)	461 (156)	4 (6)	471 (148)	407 (116)	466 (147)
PSG	486 (101)	597 (108)	3 (2)	724 (83)	473 (88)	747 (94)
CPAP Clinic	1 (1)	1 (1)	---	1 (1)	1 (1)	1 (1)
Respirologist	746 (157)	495 (169)	5205 (145)	6 (2)	771 (148)	5 (2)
Neurologist	30 (34)	145 (76)	106 (68)	27 (29)	33 (30)	27 (44)
OSA only Physician	10 (23)	7 (15)	3 (5)	8 (19)	6 (12)	4 (10)
General Internist	15 (28)	64 (57)	20 (17)	12 (28)	12 (22)	10 (25)
Psychologist	3 (2)	3 (2)	3 (1)	3 (2)	3 (2)	3 (2)
Total	1679	1773	5344	1252	1706	1263

SSAT = ambulatory sleep test; PSG = polysomnography; CPAP = continuous positive airway pressure; OSA = obstructive sleep apnea. Results are presented as mean (SD)

Table 17. Results for Base Case Scenario for the Increased Demand Case

	Baseline Demand			Increased Demand			Change	
Outcome	**Mean**	**99% CI**	**n**	**Mean**	**99% CI**	**n**	**Mean**	**99% CI**
Ttreat in the last month (days)	263	(253,274)	123 (10)	365	(354,377)	123 (15)	102	(88,116)
Urgent Patients	397	(374,420)	11 (4)	492	(466,518)	12 (3)	95	(59,131)
SDB Patients	222	(213,231)	79 (9)	330	(318,342)	80 (12)	108	(94,122)
% Change in Ttreat	30	(25,35)	---	37	(32,42)	---	7	(0,13)
Tinitial in the last month (days)	200	(193,207)	156 (10)	288	(277,298)	162 (14)	88	(78,99)
Urgent Patients	165	(156,173)	14 (4)	203	(193,213)	15 (3)	38	(25,51)
Tpsg in the last month (days)	154	(145,163)	67 (4)	205	(194,217)	67 (4)	51	(36,67)
Urgent PSG	59	(59,60)	29 (5)	59	(59,60)	29 (5)	0	(-1,1)
% Meeting CTS Guidelines	56	(53,60)	71 (8)	30	(26,34)	71 (10)	-26	(-30,-22)
High Risk Patients	7	(5,9)	39 (6)	0	(0,0)	40 (7)	-7	(-9,-5)

Ttreat = time to initiation of treatment; SDB = sleep disordered breathing; Tinitial = time to initial physician visit; Tpsg = time to initial polysomnography; PSG = polysomnography; CTS = Canadian Thoracic Society; n = mean number of patients reaching outcome (SD)

Table 18. Time to Initiation of Treatment in Last Month of Simulation for the Increased Demand Case

	Output (days)		Change (days)		N
	Mean	99% CI	Mean	99% CI	
BaseCase	365	(354,377)	---	---	123 (15)
NoTriage	331	(316,346)	-35	(-51,-18)	121 (12)
NoCPAP	745	(717,774)	380	(348,412)	89 (11)
AddMD	296	(286,305)	-70	(-84,-56)	121 (13)
AddRT	374	(363,385)	9	(-4,21)	118 (15)
AddMD_RT	301	(291,312)	-64	(-79,-49)	119 (12)

n = mean number of patients reaching outcome (SD)

Table 19. Change in Time to Initiation of Treatment over Simulation for the Increased Demand Case

	Output (%)		Change (%)	
	Mean	**99% CI**	**Mean**	**99% CI**
BaseCase	37	(32,42)	---	---
NoTriage	48	(41,56)	11	(2,20)
NoCPAP	42	(34,50)	5	(-5,15)
AddMD	36	(31,41)	-1	(-8,6)
AddRT	46	(41,52)	9	(2,16)
AddMD_RT	40	(34,45)	3	(-5,10)

Table 20. Time to Initial Physician Visit in Last Month of Simulation for the Increased Demand Case

	Output (days)		Change (days)		N
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	288	(277,298)	---	---	162 (14)
NoTriage	243	(232,253)	-45	(-56,-34)	160 (12)
NoCPAP	559	(548,570)	271	(256,286)	146 (10)
AddMD	206	(197,214)	-82	(-91,-73)	163 (16)
AddRT	292	(285,300)	4	(-7,15)	159 (12)
AddMD_RT	211	(201,220)	-77	(-86,-68)	163 (14)

n = mean number of patients reaching outcome (SD)

Table 21. Time to Initial Polysomnography in Last Month of Simulation for the Increased Demand Case

	Output (days)		Change (days)		N
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	205	(194,217)	---	---	67 (4)
NoTriage	233	(221,246)	28	(10,46)	67 (4)
NoCPAP	40	(38,41)	-165	(-177,-153)	65 (6)
AddMD	259	(247,272)	54	(39,69)	67 (4)
AddRT	200	(188,212)	-5	(-22,12)	68 (4)
AddMD_RT	272	(259,285)	67	(49,85)	68 (3)

n = mean number of patients reaching outcome (SD)

Table 22. Percentage of SDB Patients Meeting CTS Guidelines in Last Month of Simulation for the Increased Demand Case

	Output (%)		Change (%)		N
	Mean	**99% CI**	**Mean**	**99% CI**	
BaseCase	30	(26,34)	---	---	71 (10)
NoTriage	35	(30,39)	4	(-1,9)	70 (9)
NoCPAP	34	(31,37)	3	(-1,8)	52 (8)
AddMD	45	(39,50)	14	(10,19)	79 (10)
AddRT	29	(25,33)	-2	(-6,3)	70 (12)
AddMD_RT	44	(39,50)	14	(9,19)	70 (10)

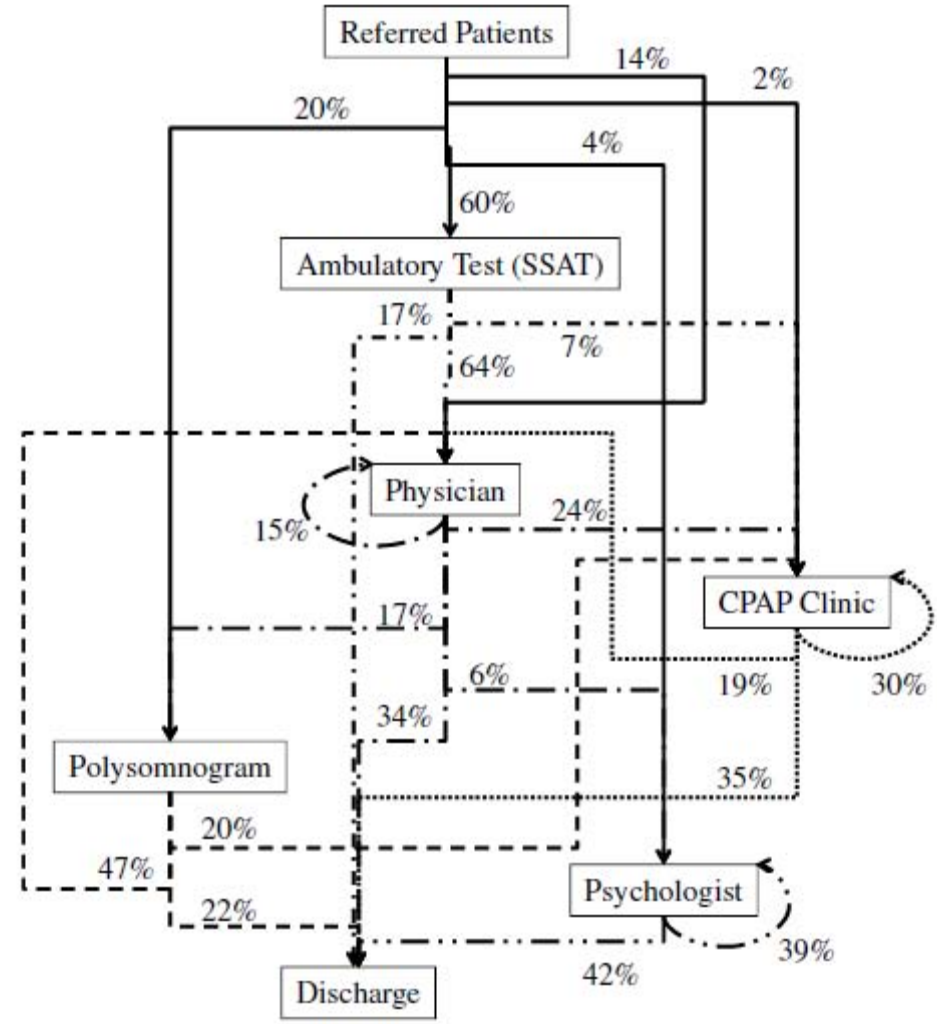
SDB = sleep-disordered breathing; CTS = Canadian Thoracic Society; n = mean number of patients reaching outcome (SD)

Table 23. Steady-State Comparison of Resource Utilization from Dataset and Model

Resource	Dataset (%)	Model (%)
SSAT	36.6	38.3
PSG	44.9	45.7
CPAP RT	73.6	79.1
Physician	46.6	41.2
Psychologist	38.0	39.9

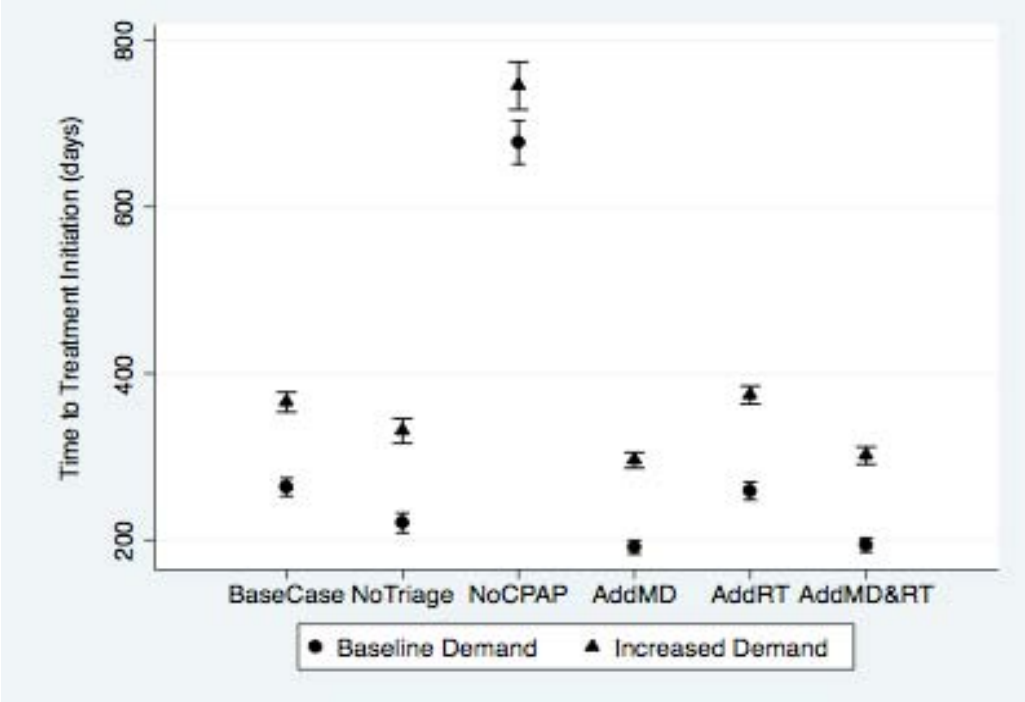
SSAT = ambulatory sleep test; PSG = polysomnography; CPAP = continuous positive airway pressure; RT = respiratory therapist.

Figure 1. Overview of Patient Flow at Foothills Sleep Centre



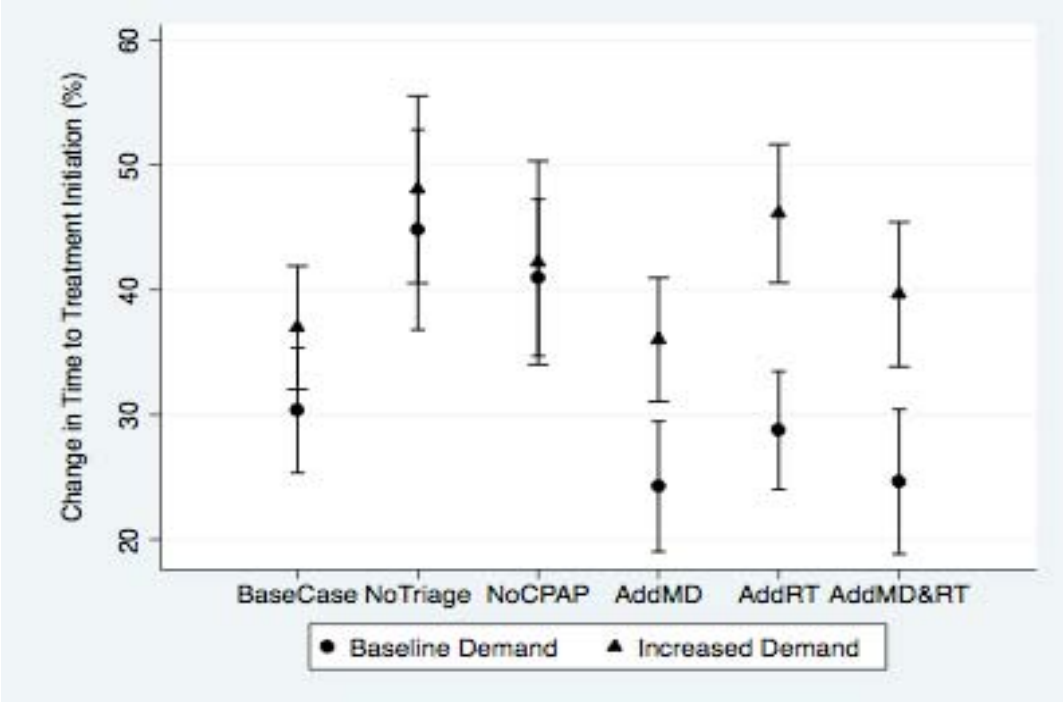
Lines represent patient flow after any visit to the named process: —— Referred Patients; - - - SSAT; — · Physician; ····· CPAP Clinic; - - · Polysomnogram; — · · Psychologist . For simplicity, the pathways presented are limited to those that are clinically most important; thus, percentages may not sum to 100%.

Figure 2. Time to initiation of treatment in last month of simulation for scenarios under baseline and increased demand



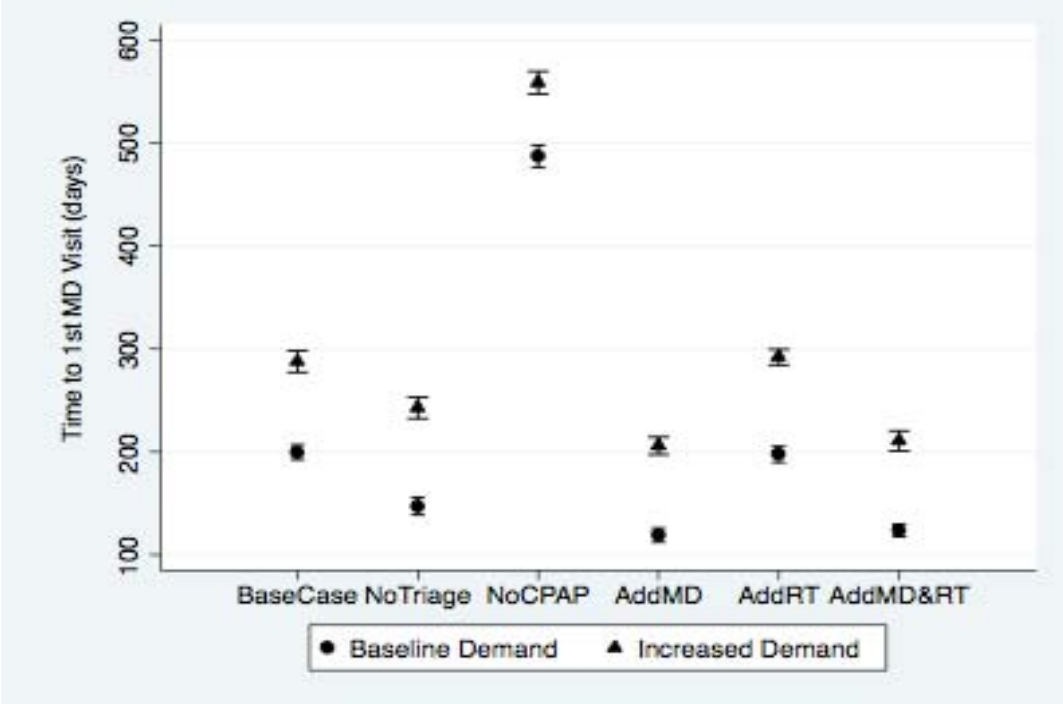
Results are presented as mean +/- 99% CI. Confidence limits are represented by short markers for the Baseline Demand Case and long markers for the Increased Demand Case.

Figure 3. Change in time to initiation of treatment in last month of simulation for scenarios under baseline and increased demand



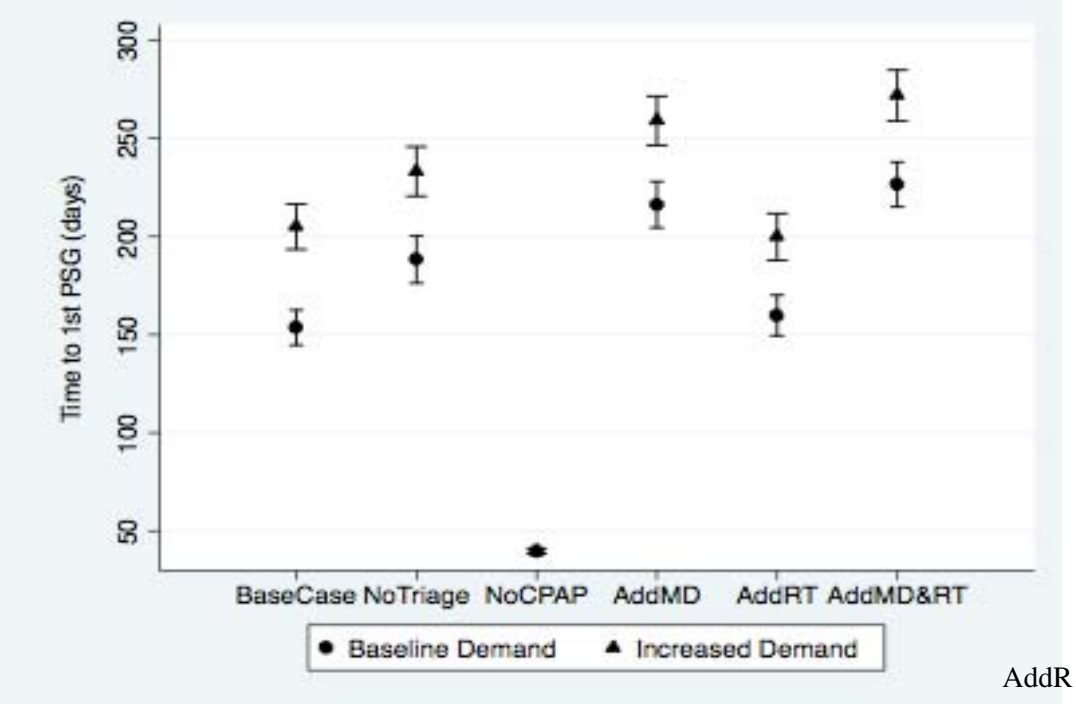
Results are presented as mean +/- 99% CI. Confidence limits are represented by short markers for the Baseline Demand Case and long markers for the Increased Demand Case.

Figure 4. Time to initial physician visit in last month of simulation for scenarios under baseline and increased demand



MD = physician. Results are presented as mean +/- 99% CI. Confidence limits are represented by short markers for the Baseline Demand Case and long markers for the Increased Demand Case

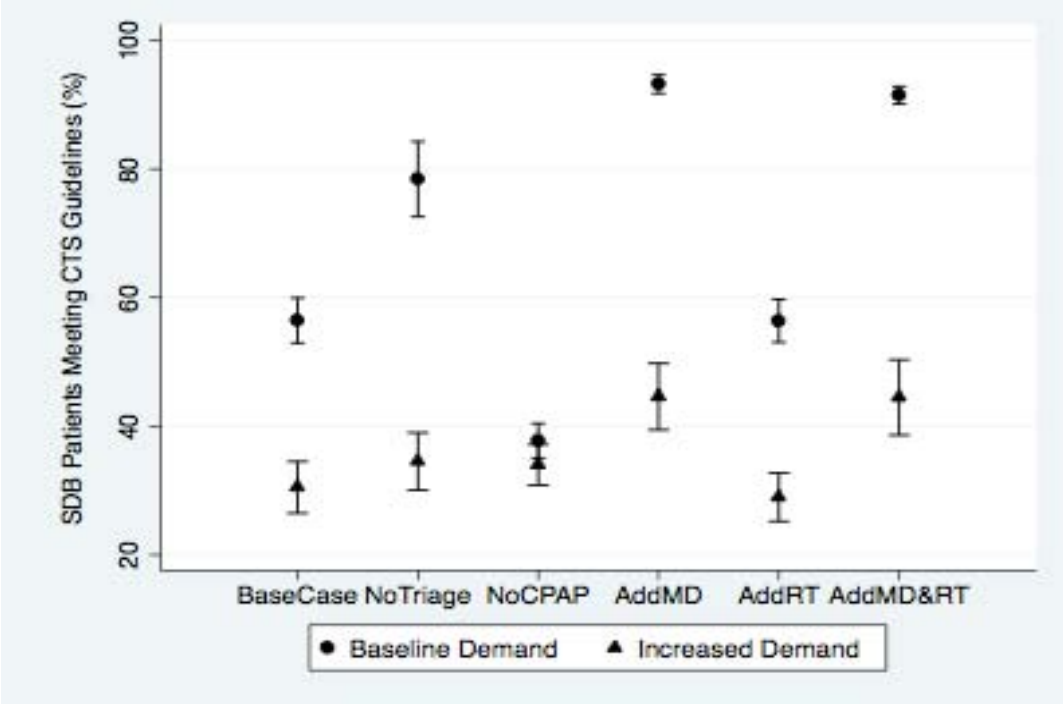
Figure 5. Time to initial polysomnography in last month of simulation for scenarios under baseline and increased demand



AddR

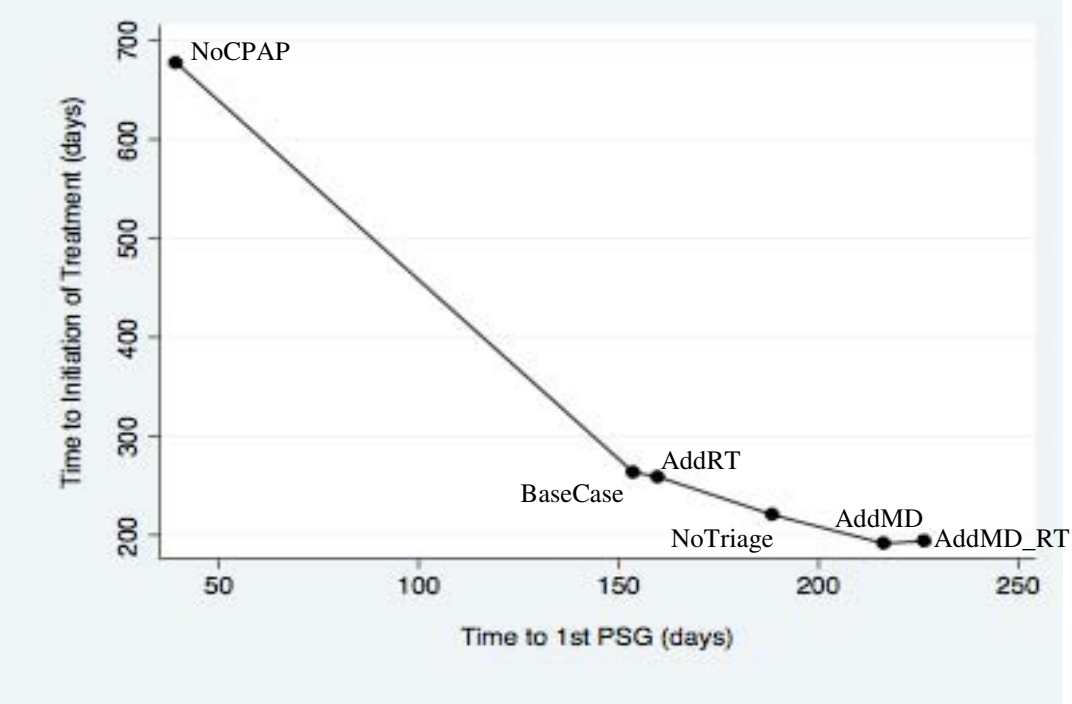
PSG = polysomnography. Results are presented as mean +/- 99% CI. Confidence limits are represented by short markers for the Baseline Demand Case and long markers for the Increased Demand Case.

Figure 6. Percentage of patients with sleep-disordered breathing meeting Canadian Thoracic Society guidelines for scenarios under baseline and increased demand



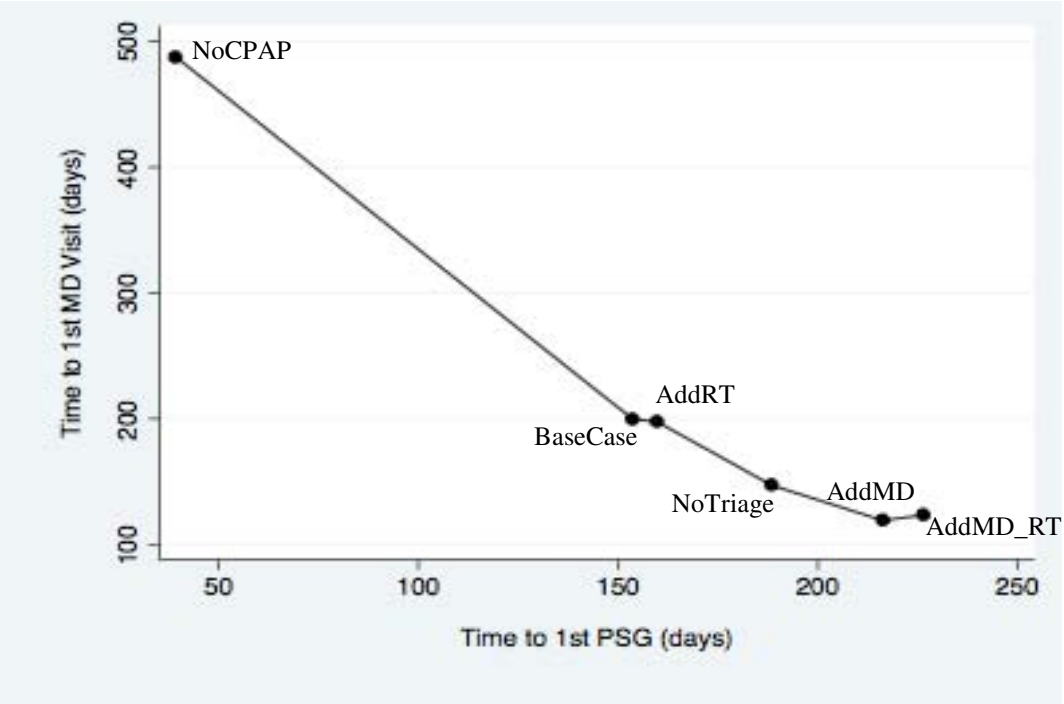
CTS = Canadian Thoracic Society; SDB = sleep-disordered breathing. Results are presented as mean +/- 99% CI. Confidence limits are represented by short markers for the Baseline Demand Case and long markers for the Increased Demand Case.

Figure 7. Tradeoff curve for time to initiation of treatment versus time to initial polysomnography for scenarios under baseline demand



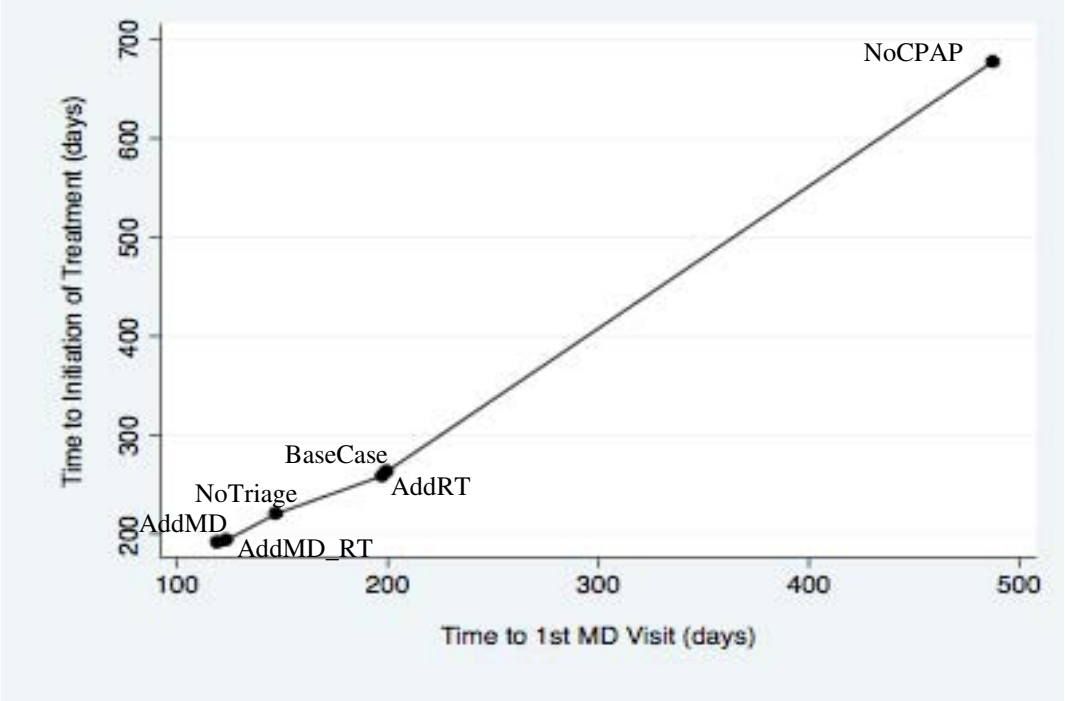
PSG = polysomnography

Figure 8. Tradeoff curve for time to initial physician visit versus time to initial polysomnography for scenarios under baseline demand



MD = physician; PSG = polysomnography

Figure 9. Tradeoff curve for time to initiation of treatment versus time to initial physician visit for scenarios under baseline demand



MD = physician

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Appendices

Appendix A: Process Description of Foothills Sleep Centre

Referral and Triage

Resources: Triage coordinator, Referral clerk

Patients arrive to the sleep centre (SC) through the referral and triage process or are referred for diagnostic testing only by non-sleep respirologists. Some patients who are referred for testing only are subsequently assessed by a sleep physician without passing through the referral and triage process.

When the referral is received, demographic data is entered by a referral clerk into the Clinic Information System (CIS) and the referral is triaged by the triage coordinator. The triage coordinator assesses the referral for urgency based on pre-specified clinical criteria. Referrals that are classified as 'primary urgent' are immediately booked for urgent assessment by a physician.

At the beginning of the following month, patients that are not classified as 'primary urgent' are sent a sleep questionnaire to complete. Questionnaires may be completed online or in paper form depending on patient preference. Patients will not be added to the waiting list unless the completed questionnaire is received. Patients are reminded monthly to complete the questionnaire, and are discharged from the SC if no questionnaire is received within 1 month of the second reminder. When the questionnaire

is returned, the triage coordinator assigns a secondary triage category of urgent, semi-urgent, or normal. This urgency rating is based upon pre-specified clinical criteria. The triage coordinator also assigns a patient type depending on the likely clinical diagnosis. These diagnostic categories, and the types of SC physicians who may be assigned to patients in this category, are listed below:

- Obstructive sleep apnea (OSA) - any physician
- Insomnia - psychologist
- Intrinsic sleep disorders (not breathing-related) - respirologist, general internist, neurologist
- Respiratory disease or complex sleep-disordered breathing - respirologist
- Seizures or neurological disease - neurologist
- Chronic fatigue - respirologist, general internist

The triage coordinator indicates whether the patient needs an ambulatory sleep test (SSAT). At the SC, almost all patients who have not recently had a SSAT undergo a SSAT before being assessed. These patients are then added to the waiting list.

Ambulatory Sleep Test (SSAT)

Resources: SSAT machine, SSAT clerk, Referral clerk

Patients arrive at the SSAT process from the referral and triage process, from non-sleep respirologists, or from practitioners within the SC. Patients referred for testing from non-sleep respirologists leave the SC immediately after testing, but may return for follow-up

testing, advanced sleep testing (i.e. polysomnography (PSG)), or for assessment by a sleep physician if referred after the SSAT test.

There are 11 available SSAT machines, nine of which are available for regular outpatient use and one of which is reserved for testing of 'secondary urgent' patients if another machine is not available. The 11th machine is used for demonstration of the machine's use to patients. The failure rate for these machines is negligible.

New patients from the referral and triage process are scheduled for a prescreen SSAT by a referral clerk, and the test must occur no more than 8 weeks before clinician assessment. Since waiting times are higher for physicians than for SSAT testing, the SSAT is not scheduled unless the physician appointment is available. All other tests, including rebooked tests for new patients, are scheduled by the SSAT clerk. Tests for returning patients or tests that were ordered by a non-sleep respirologist are scheduled up to 1 month in the future. If applicable, the SSAT clerk also schedules the clinical visit following the SSAT when the SSAT appointment is scheduled. SSAT slots are scheduled on a first-come, first-served basis.

Patients arrive on the day of their test and receive instruction on the use of the SSAT machine. This instruction is provided each weekday by the SSAT clerk, and the testing occurs that night. Patients return the machines to the SC on the following weekday morning. Cancellations and no-shows are rescheduled as soon as possible, to a maximum of 3 cancellations or 3 missed appointments before a patient is discharged from the SC.

The tests are interpreted by a sleep physician within seven days. SSAT interpretation does not delay patient appointments that are scheduled to follow the SSAT.

Physician/Psychologist Appointments and Front Desk

Resources: Physician/Psychologist, Front Desk or Referral clerk

Patients arrive for assessment by a sleep physician or psychologist through referral and triage, by direct referral from a non-sleep respirologist, after inpatient diagnostic testing, or in follow-up of a previous assessment. Depending on which process the patient last passed through, physician and psychologist appointments are scheduled by clerks from the referral and triage process, SSAT, PSG or front desk.

New patients are scheduled for provider appointments based on urgency criteria and time in queue. 'Primary urgent' patients are scheduled with highest priority in the first available clinic slot for the specified physician type and do not undergo a SSAT. 'Secondary urgent' patients are scheduled with similar priority, but may have SSAT testing before seeing the provider.

Semi-urgent and normal urgency patients are scheduled in priority sequence once urgent patients have been scheduled, depending on physician availability. The scheduling horizon for new patients is approximately two months. A patient will be called three times and if no response is obtained, a discharge letter is sent to the referring physician. No further scheduling attempts are made, and the patient is removed from CIS.

Appointment slots for each provider are grouped into half-day clinics, which occur on the same day(s) each week for each provider as follows:

MONDAY	TUESDAY	WEDNESDAY	THURSDAY	FRIDAY
GenIntMD 8:30 – 12:00 NEW 30 F/U 15	**GenIntMD** 9:00 – 12: 00 NEW 30 F/U 15	**RespMD** 9:00 – 12:00 NEW 30 F/U 30	**OSAonlyMD** 9:00 – 12:00 NEW w SSAT 45 NEW w/o SSAT 30 FU 15	**RespMD** 9:15 – 11:30 NEW 45 F/U 15
RespMD 9:00-12:00 NEW 45 F/U 30	**Psych** 9:00-1:00 NEW 60 F/U 60	**RespMD** 9:00 – 12:00 NEW 30 F/U 30	**Psych** 9:00-1:00 NEW 60 F/U 60	**RespMD** 9:00 – 12:00 NEW 30 F/U 15
Psych 9:00-1:00 NEW 60 F/U 60				**Psych** 9:00-1:00 NEW 60 F/U 60
NeuroMD 1:30 - 4:00 NEW 45 F/U 30		**RespMD** 1:00 – 4:00 NEW 45 F/U 15		
		RespMD 1:00 – 4:00 NEW 30 F/U 30		

Space constraints result in a maximum of two clinics per half-day within the SC, although the psychologist and one of the respirologists conduct clinics in other areas of the hospital. Time allotments for appointments are as follows:

- Respirologist (RespMD) - varies by practitioner - 30 or 45 minutes for new, 15 or 30 minutes for follow-up

- Neurologist (NeuroMD) - 45 minutes for new, 30 minutes for follow-up
- Physicians who only treat sleep apnea (OSAonlyMD) - 30 minutes for new, 15 minutes for follow-up
- General Internist (GenIntMD) - 30 minutes for new, 15 minutes for follow-up
- Psychologist (Psych) - 60 minutes for new and follow-up

Some clinics contain reserved slots, which are listed below. For respirologists and general internists, the slots may be released for the scheduling of any patient if the appointment is less than 1 week away. Psychologist reserved slots are only released in rare circumstances.

- Respirologists - 1 urgent new slot/week, 2 new (Monday), 6-8 new (Wednesday), 4-5 new (Friday) slots
- General Internist - 4 new slots/clinic
- Psychologist - 2 follow-up slots/clinic

Patients are scheduled on a first-come first-served basis, with follow-up patients taking priority over new patients if two requests are received simultaneously. The availability of clinics is dictated by individual physicians based on on-call duties and vacation, and is usually determined at least three months in advance.

If a patient calls to cancel an appointment, the clinic slot is preferentially filled by a new urgent or semi-urgent patient provided the prescreen SSAT can be performed in advance if needed. If no such patient is available, then follow-up patients are scheduled from a cancellation list. When a patient cancels an appointment, an attempt is made to

reschedule the appointment at the time of cancellation; patients who cannot commit to another appointment time are given two weeks to reschedule, at which point they are again contacted by the front desk or referral clerk to schedule an appointment. Patients who cancel or fail to attend scheduled appointments on three occasions are discharged from the clinic.

After the provider's assessment, patients may be scheduled for further testing, clinical follow-up or CPAP clinic assessment. CPAP clinic assessment may occur on the same day and are classified as 'drop-in' visits (see *CPAP Clinic* below). Any scheduled follow-up visits may incorporate an 'obligatory delay', whereby the provider specifies a delay before the next follow-up visit should occur. These delays are to ensure that all necessary testing is completed or to assess the patient's response to treatment. Other dispositions include referral to another provider or discharge from the clinic.

Overnight Polysomnogram

Resources: PSG Technologist, PSG bedroom, PSG Clerk

Polysomnography (PSG) is an advanced diagnostic sleep test ordered by sleep physicians in the inpatient and outpatient setting. PSG testing may be ordered by any sleep physician, but can only be interpreted by sleep respirologists, the neurologist or one of the physicians who only see patients with OSA. Respirologists may order PSG tests on behalf of other non-sleep respirologists, even without a formal referral to the SC. Patients who undergo PSG typically have a sleep disorder that cannot be identified by

SSAT, or require in-laboratory monitoring during initiation of treatment for complex or severe sleep-disordered breathing.

There are four bedrooms available for clinical testing, in which one patient can undergo testing in each bedroom each night. Therefore, four clinical tests are scheduled for each night, from Sunday through Thursday. There are two technologists working each night, each of whom is allocated two patients. Each night, a maximum of three slots can be used for patients with possible hypoventilation. These patients require extra monitoring and attention from the technologists. One slot on each day is reserved for an urgent inpatient or outpatient test. The patients who use these slots are typically patients in whom hypoventilation is suspected. The remaining slot is used for any indication. A third technologist is scheduled every Thursday and two Wednesdays per month. On these nights, up to four hypoventilation patients will be scheduled. If an urgent patient is not scheduled by the day of the test, the urgent slot will be released for the scheduling of a non-urgent patient. The limit of possible hypoventilation patients is still obeyed when this urgent slot is released for scheduling of non-urgent patients.

Outpatient tests are scheduled based on the urgency rating indicated on the requisition. The scheduling horizon is 30 days. If patients cannot be reached by telephone, a letter is sent to the patient with instructions to call the PSG laboratory to schedule a test. If another one or two months passes and the patient has not called to be scheduled, then the chart is sent back to the ordering physician for review. Usually, the patient is discharged from the clinic by the ordering physician. Follow-up physician appointments are

scheduled with the PSG appointment by the PSG clerk when the PSG appointment is scheduled. Follow-up appointments are scheduled for at least one month after the PSG, to allow time for scoring by PSG technologists and physician interpretation.

Cancelled appointments are preferentially filled based on urgency, using a cancellation list. If a patient does not arrive for the test, the slot is unfilled for that night. Cancelled and missed tests will be rescheduled with high priority. The ordering physician is notified if a patient cancels three test appointments or misses two tests and the patient is usually discharged from the SC.

Some patients who undergo PSG are seen by a CPAP therapist the next morning to initiate treatment; these visits do not alter the scheduling of PSGs. Some also stay the next day for a Mean Sleep Latency Test (MSLT). This test consists of a series of timed naps, and objectively demonstrates the patient's sleepiness. The patient uses the same room and one PSG technologist administers the test while performing regular daily duties (see below). Up to two MSLT tests can be performed on Monday and Tuesday, and one MSLT can be performed on Thursday.

PSG technologists score the test within seven days of completion, after which the interpreting physician will provide a clinical interpretation within one week. Scoring and interpretation of tests usually does not delay the patient's subsequent appointments. If a test is deemed to be of unacceptable quality, repeat testing may be ordered on short notice. These repeat tests are scheduled with high priority.

CPAP Clinic

Resources: CPAP respiratory therapist, CPAP clinic coordinator, Front Desk, SSAT or PSG clerk

The CPAP clinic is an alternate care provider clinic designed to address issues related to the initiation and use of positive airway pressure (PAP) therapy. These are treatments for OSA and other types of sleep-disordered breathing. Patients arrive to the CPAP clinic by referral from sleep physicians, through the referral and triage process, or by self-referral.

New referrals through the referral and triage process (called 'CPAP Reassess') are prioritized according to the same criteria as for physician appointments. They are reviewed with the CPAP clinic coordinator for appropriateness before being assigned 'CPAP Reassess' status. These patients all undergo a SSAT before the CPAP clinic appointment if they have not had one recently. New referrals from sleep physicians (called 'New') are usually assessed as 'drop-in' visits by the respiratory therapists (RT) working in the CPAP clinic on the day of the physician visit. Alternatively, 'New' visits may occur on the morning after PSG testing. Finally, a sleep physician may refer a patient from his/her practice outside the SC (called 'ACP New').

There are two CPAP therapists in the clinic each weekday. Appointments are scheduled in half-day clinics on six half-days per week. In addition, 'drop-in' patients may arrive throughout the day after a physician clinic visit. On four half-days, which coincide with two simultaneous physician clinics in the SC, no scheduled appointments are available and all visits are 'drop-in' visits. On CPAP clinic days on which scheduling is possible,

appointments are scheduled using a first-come first-served priority rule with variable appointment lengths depending on the purpose of the visit. These appointment types and durations are listed below:

- New PAP start - 15 minutes
- CPAP Reassess - 90 minutes
- Routine Follow-up - 60 minutes
- PAP Troubleshoot - 60 minutes
- TLC for PAP - 90 minutes
- ACP New - 90 minutes
- Long-term Follow-up (see below) - 15 minute equipment check + 90 minute visit (appointments occur on separate days)

When physician clinics are cancelled by the physician (at least 90 days in advance), the availability of scheduled CPAP appointments will be increased for that day since the load of 'drop-in' patients will be decreased. Visits are scheduled by CPAP RTs or front desk clerks unless the CPAP clinic appointment follows a test. In this case, the follow-up appointment is scheduled by the clerk associated with that test process. Some patients are seen the morning after PSG to initiate CPAP therapy; these visits do not alter the scheduling of PSGs, and are 'drop-in' visits.

The CPAP clinic uses a computerized tracking system to ensure that patients have started treatment, have undergone follow-up testing, or for telephone follow-up visits. A CPAP therapist is scheduled for six hours on three days per week to perform these duties. There

is no urgency classification for patients in the tracking system, but sicker patients are contacted at shorter time intervals for closer follow-up.

If a patient is contacted three times without a response or returned call, then a discharge letter is sent to the referring physician. When a patient cancels an appointment, an attempt is made to reschedule the appointment at the time of cancellation; patients who cannot commit to another appointment time are given two weeks to reschedule, at which point they are again contacted by the SC to schedule an appointment. If a patient does not attend an appointment, the appointment is rescheduled as soon as possible. Three cancellations or missed appointments result in a discharge letter sent to the referring physician. No further appointments are scheduled and the patient is discharged from CIS.

If a patient has ongoing medical problems or severe sleep-disordered breathing, the physician or CPAP therapist may recommend the long-term follow-up (LTFU) pathway once the patient is clinically stable. These patients are assessed after 3 months and then annually. LTFU patients undergo SSAT testing before each annual CPAP clinic visit. It is anticipated that LTFU patients will be followed indefinitely, whereas all other patients will ultimately be discharged once they meet pre-specified CPAP clinic discharge criteria. These discharge criteria are based on indicators of clinical response to treatment, and may result in multiple visits for patients who are having difficulty with PAP therapy.

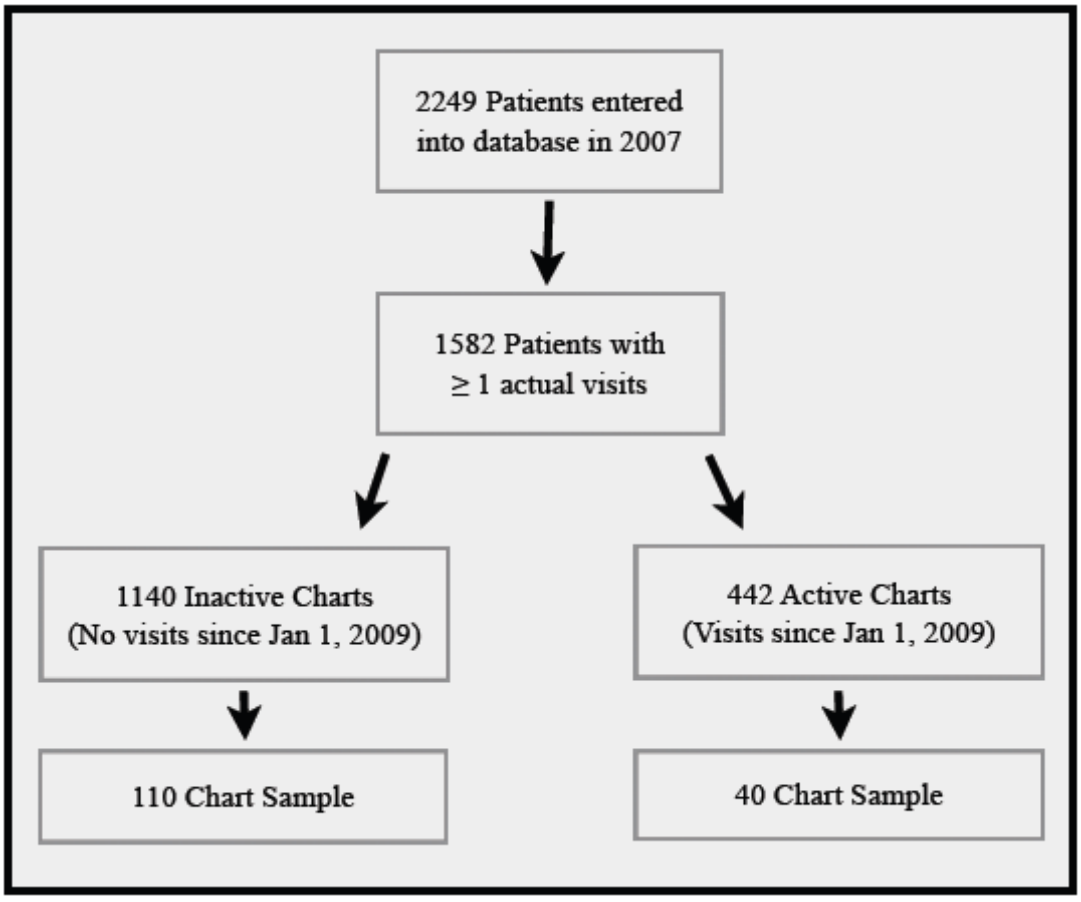
Other responsibilities of the CPAP therapists are to fax any documentation regarding PAP therapy to home-care companies, insurance companies, or governmental social assistance programs. Additionally, the CPAP therapists will provide letters for patients' insurance companies outlining their diagnosis and therapy, and will also help coordinate oxygen therapy for clinic patients. This work is called "Professional Consult", and adds a significant load to the daily work of each therapist.

Appendix B: Data Description for Foothills Sleep Centre DES Model

Dataset

Sampling frame is all patients first entered in Clinic Information System (CIS) in 2007

- Exclusions:
  - Patients seen prior to 2007 and re-referred
  - Patients referred in 2007 but not seen for ≥ 15 months
  - Patients who did not attend provider visits or tests (n = 667)



Description of dataset

- 150 patients sampled from active and inactive lists (see figure above)
- 132 (88%) patients had at least 1 provider visit
- 120 (80%) patients had at least 1 physician visit
- 52 (35%) had at least 1 polysomnogram
- 11 (7%) had no outcome visit (all had SSAT test only)

Characteristic	2007 Dataset	%
Referral Status		
Referred	115	77*
Not Referred	35	23*
Total Patients	150	100
Urgency		
Primary Urgent	11	10
Secondary Urgent	27	23
Semi Urgent	27	23
Normal	50	43
Total with Urgency	115	100
Occupational Risk	9	8
Epworth Sleepiness Scale	11	---
Patient Type		
Any (OSA)	63	55
Insomnia	9	8
RLS, PLMD, Narcolepsy	13	11
Respiratory	28	24
Neurologic	1	1
Chronic Fatigue	1	1
Total with Patient Type	115	100

SSAT = ambulatory sleep test; OSA = obstructive sleep apnea; RLS = restless legs syndrome; PLMS = periodic limb movement disorder.
*Percentages calculated using total dataset whereas other percentages calculated based on number of referred patients only.

- Comparison of 2007 Dataset with Jan 2008 - Aug 2010 Visits

Visit Type	2007 Dataset		2008-10 Data		
Diagnostic Tests	**Count**	**%**	**Count**	**%**	**p value**
SSAT	130	65	4501	63	0.68
PSG	71	35	2617	37	0.68
Totals	201	100	7118	100	---
Provider Visits					
CPAP Clinic	111	28	3777	37	<0.001
Respirologist	137	35	2928	29	0.008
Neurologist	4	1	192	2	0.21
OSA only Physician	53	13	845	8	<0.001
General Internist	43	11	1265	12	0.39
Psychologist	47	12	1261	12	0.82
Totals	395	100	10268	100	---

SSAT = ambulatory sleep test; PSG = polysomnography; CPAP = continuous positive airway pressure; OSA = obstructive sleep apnea. P values are for a two sample t-test.

Other Input Data (see Approximations Summary for numerical approximations)

Weekly arrival rate based on new referrals and re-referrals

- New Patients (n = 5849)
    - Entered in database Jan 1, 2008 - Dec 31, 2010 (n = 7720)
    - Excluded deleted patients who did not return questionnaire (n = 1871)
        - These patients do not contribute to system demand
- Re-referrals (n = 2042)
    - ≥ 1 visit from Jan 1, 2008 - Dec 31, 2010
    - Entered into database before 2008
    - No visits Jul 1, 2006 - Dec 31, 2007
        - If entered before 2008 and had a visit during July 2006 – December 2007,, they were probably active patients; if no visit during these dates, then

probably re-referred since most patients have at least 1 visit/year (so definitely 1 in 1.5 years)

- Total weekly arrival rate = 50.8
    - **Used 51 referrals/week**

No-show/cancellation rates taken from Jan 1, 2008 - Aug 31, 2010 data

- No-show rate = # of No-shows/(# No-shows + # Visits)
- Cancel rate = # Cancellations/(# Cancellations + # Visits + # No-shows)

Weekly clinic schedules based on current (2011) schedule

Clinic cancellations by MD based on Jan 1, 2008 - Dec 31, 2010 data

- Probability = # clinics actually held/# clinics if full capacity

Known Data Issues

- No information on sleep diagnosis, comorbidity, medications
- Don't know the distribution of intervals between follow-up visits
- Time required for CPAP "Professional Consult" work is not available
- Delays due to difficulties contacting patients for appointments not available

Appendix C: Simplifying Assumptions for Foothills Sleep Centre DES Model

General

- No delays for processing referrals, requisitions, etc.
- Desired follow-up interval for visits AFTER the outcome visit are rounded down from the actual inter-visit interval to the nearest of 1,2, 3, 6, or 12 months
    - Exception: 2nd MD visit if it is an outcome visit - desired interval is 6 weeks after 1st visit
    - These intervals incorporate obligatory delay requested by provider and appointment delays due to cancellations, missed appointments or patient preference
- Scheduling of visits occurs after previous process is complete - no linked scheduling
    - May underestimate system performance as patients enter queues later
- Ignore delays due to difficulty contacting patient - no data on these delays
- Patients are always available for appointment slots
    - No patient preference for appointments
- Probability of missed or cancelled appointment is independent of previous no-shows/cancellations
- Ignore cancellation list - all patients available for cancelled slots
- No seasonality to clinic schedules (i.e. Sleep centre functions 52 weeks/year)

    - Will slightly overestimate system performance by excluding seasonal/statutory holidays
- All clerical and booking staff are always available
    - Clerical functions not interrupted by holidays/illness in the actual system

Referral & Triage

- No delay from receipt of referral to primary triage assessment
    - These dates normally differ by a maximum of a few days in the actual system
- All questionnaires sent on 1st of month after referral received
    - Generally sent within 3-5 days before or after this date in the actual system
- No difference in questionnaire return date between paper and online questionnaires
    - In actual system, the questionnaire date and questionnaire return date may differ slightly for written questionnaires
- Questionnaire return rate/delay is independent of clinical characteristics, urgency

SSAT

- 9 machines ALWAYS available
    - 10th machine for urgent patients assumed not available (can add if needed in future model configurations)
- All tests are 1-night studies
- No delay for test to be interpreted
    - Does not delay appointments/flow in actual system

- Ignore repeat testing for poor quality test

Front Desk/MD or Psych Visit

- Physicians are grouped by expertise and types of patients seen - there may be multiple physicians captured by an MD group
- Patients are scheduled for the next available clinic slot within an MD group - no continuity of care by a single provider
- Provider scheduling horizon is 90 days
- Each day, fixed probability that a clinic will be cancelled for 91 days in future
    - Probability differs for each provider group
- 1 urgent slot reserved in respirologist clinic on Wednesday
    - The day of the week on which this urgent slot is reserved varies
- Allocation of new/FU patients and time allotment is the same for all physicians in each MD group
    - For respirologists, depends on day of week
        - New: 45 min on Mon/Fri, 30 min on Wed
        - F/U: 30 min on Mon/Wed, 15 min on Fri
- Scheduling occurs at 14:40 (0.6 of day), after arrivals/cancellations for that day have occurred
    - Same-day cancellations after 14:40 are unfilled (considered no-show)

PSG

- Only 4 PSG beds available each night - 5th bedroom is for research only

- Triage of PSG requisitions
    - No revision of urgent requisitions by PSG manager
    - New tests are urgent or normal, follow-ups are all normal
- Inpatients not differentiated from urgent outpatients
- Ignore reserved slots for urgents/inpatients
    - All urgent patients usually have PSG within 1 month, so expect slightly worse but still short delays
- Ignore repeat testing for poor quality test
- All tests requiring TcCO2 (possible hypoventilation) are 'complex' - max 3/night unless 3 techs (then 4/night)
    - 3 PSG technologists available on Thursday only - ignore extra technologist on every alternate Wednesday
- 5 MSLT slots available per week (ignore rare possibility of 6/week)
- Add 1 month for scoring/interpretation
    - May also worsen primary outcome (T_{Treat}) because of no linked scheduling (see *General* above)

CPAP Clinic

- Ignore processing and phone calls for patients who self-refer (2-3/year)
- No scheduled appointments during 'drop-in' clinics
- Post-PSG CPAP visit considered a 'drop-in' visit
    - May be a scheduled CPAP visit, but never interferes with PSG scheduling

- Probability of being deemed suitable for telephone visit is independent of clinical characteristics
- All phone visits are made at the time of the first call (no messages left for patients)
    - Will overestimate system performance since difficulty contacting patients often delays outcomes in actual system
- LTFU annual equipment check on day of appointment rather than at time of SSAT
    - Difference is usually ~ 2 weeks in actual system,
- LTFU appointments do not follow the 3-month, then 12-month follow-up interval
    - Used follow-up interval as described in *General* above
- CPAP RTs always available as scheduled

Assumptions for Alternative Scenarios

- NoTriage scenario
    - No questionnaire process - all triage information is in referral letter
- NoCPAP scenario
    - All visits to CPAP are replaced by visits to the provider who last saw the patient
    - If no other provider visits, visits removed if ACP new (off-site referral) or replaced by assigned MD if CPAP R/A
- Extra MD scenario
    - 2 reserved slots for new patients

    - 30 min for new and follow-up
    - No adjustment to CPAP since drop-in RT already available
- Extra CPAP RT scenario
    - RT available for booked slots and drop-in
- Extra MD and CPAP RT scenario
    - All assumptions as for individual Extra MD and Extra RT scenarios

Appendix D: Approximations Summary for Foothills Sleep Centre DES Model

Process	Approximation	Rationale
Referral/Triage		
Arrival Rate	Mean 51 patients/week	2008-10 arrival data + re-referrals (see Data Description)
SSAT		
Cancellation Rate	14.71%	2008-10 Clinic Data
No-Show Rate	4.98%	2008-10 Clinic Data
Delay to Cancellation	Unif(0,aSSATSchedDate-TNOW)	No data
PSG		
Cancellation Rate	10.93%	2008-10 Clinic Data
No-Show Rate	2.42%	2008-10 Clinic Data
Delay to Cancellation	Unif(0,aPSGSchedDate-TNOW)	No data
CPAP		
Cancellation Rate	14.82%	2008-10 Clinic Data
No-Show Rate	5.86%	2008-10 Clinic Data

Professional Consult Workload	12 hours daily, divided among RTs	Meeting with CPAP therapists
OK for Phone - 1st visit	15.00%	Approximation by CPAP Clinic Manager
OK for Phone - 2nd visit	39.60%	2008-10 Clinic Data (excluding Professional Consult)
OK for Phone - 3rd visit	52.10%	2008-10 Clinic Data (excluding Professional Consult)
Time required for Drop-in visit	Tria(15,30,60) minutes	Approximation by CPAP Clinic Manager
Delay to Cancellation	Unif(0,aCPAP_VisitSchedDate-TNOW)	No data
RespMD		
Cancellation Rate	33.26%	2008-10 Clinic Data
No-Show Rate	7.58%	2008-10 Clinic Data
Delay to Cancellation	Unif(0,aRespMD_VisitScheddate-TNOW)	No data
Probability of Clinic Cancellation	15.45%	2008-10 Clinic Data
NeuroMD		
Cancellation Rate	40.11%	2008-10 Clinic Data
No-Show Rate	8.13%	2008-10 Clinic Data

Delay to Cancellation	Unif(0,aNeuroMD_VisitScheddate-TNOW)	No data
Probability of Clinic Cancellation	37.74%	2008-10 Clinic Data
OSAonlyMD		
Cancellation Rate	32.80%	2008-10 Clinic Data
No-Show Rate	4.52%	2008-10 Clinic Data
Delay to Cancellation	Unif(0,aOSAonlyMD_VisitScheddate-TNOW)	No data
Probability of Clinic Cancellation	58.07%	2008-10 Clinic Data
GenIntMD		
Cancellation Rate	28.50%	2008-10 Clinic Data
No-Show Rate	6.43%	2008-10 Clinic Data
Delay to Cancellation	Unif(0,aGenIntMD_VisitScheddate-TNOW)	No data
Probability of Clinic Cancellation	8.49%	2008-10 Clinic Data
Psych		
Cancellation Rate	25.25%	2008-10 Clinic Data
No-Show Rate	7.21%	2008-10 Clinic Data
Delay to Cancellation	Unif(0,aPsych_VisitScheddate-TNOW)	No data

Probability of Clinic Cancellation	4.40%	2008-10	Clinic Data

Appendix E: Model Purpose & Data Structure for Foothills Sleep Centre DES Model

N.B. This document is intended to accompany the process description (Appendix A), data description (Appendix B) and list of simplifying assumptions (Appendix C).

Overview and Purpose

The Foothills Sleep Centre (SC) is a multidisciplinary academic sleep centre that provides both ambulatory and in-laboratory diagnostics as well as medical care for a variety of sleep disorders. Approximately 5000 patient visits occur each year. Current waiting times for initial assessment exceed one year for non-urgent referrals. Meetings with stakeholders at the SC have further identified the time to the initiation of therapy as an important access-related outcome. Thus, model conceptualization, construction and perturbations are driven by this performance measure.

The SC is comprised of five major processes, all of which are represented in the model. These include referral and triage (R&T), ambulatory testing (SSAT), clinician assessment, polysomnography (PSG), and an alternate care provider clinic (CPAP). Newly referred patients may take any number of paths through some or all processes, including repeat encounters at the PSG, SSAT, clinician assessment or CPAP processes.

Conceptual Model/Data Structure

NB: <process> is a generalization of all processes in the DES model, and is replaced with the corresponding process name in the model. Similarly, <provider> refers to the CPAP clinic, physician or psychologist processes

Entities

There are seven entity types in the model. The first type, patients, enter the model in a number of ways. If referred by another physician for assessment by a sleep practitioner, most patients pass through R&T. Depending on the information provided with the referral, the patient may be rated as 'Primary Urgent' (aPrimUrg) and be sent for highest priority scheduling with a physician. All remaining R&T patients are sent a survey on the 1st of the next month (delay of 31-CalDayOfMonth(TNOW) days) which is returned within 3 months (delay represented by aQuestionnaireDelay). The patient is assigned an urgency rating (aUrgency) of 'urgent', 'semi-urgent' or 'normal' based on clinical data that is provided by the patient through the questionnaire (including but not limited to aEpworth, aOccRisk). These patients are also assigned a patient type that helps identify a provider with the appropriate expertise for their likely sleep diagnosis (aProvType), and the requirement for a SSAT is indicated if one has not been performed before referral (aSSATdone==0). These assignments dictate the clinical pathways and priorities for a patient. A few patients bypass the R&T process under special circumstances (aRefTriage==0); these patients typically have severe sleep-disordered breathing and are assigned to a respiratory physician. Patients are also referred for sleep testing by certain non-sleep physicians, and usually leave the sleep centre after testing is complete. No

clinical information is available for these patients. All patients are assigned a referral date (aArrTime) for the purposes of measuring time intervals to later points in the model.

As patients continue through the model, there are other important characteristics that are captured as attributes. Since the time to initiation of treatment is the basis for the primary outcome measures, patient entities are assigned a visit number for each process that will increment each time the patient flows through that process (a<process>Number for tests and a<process>_VisitNumber for provider visits). Secondary outcomes can be determined using visit numbers for clinician visits and PSG. After each visit that qualifies as an outcome visit, the model will capture the relevant outcome measures (through record modules and output statistics) Attributes indicating sleep testing results (aFirstSSATRDI, aFirstPSGAHI) will be used to identify patients with sleep-disordered breathing within the model.

Process-specific attributes such as the date an appointment or test was requested (a<process>ReqDate), how much time is needed for a provider appointment (a<provider>Num15minslotsNeeded), or whether any special resources are needed (aPSGTcCO2, aPSGMSLT), are all used for queueing and scheduling. Once an appointment is scheduled, the patients wait until the scheduled appointment date (delay of a<process>SchedDate-TNOW). If a patient cancels or does not attend an appointment (probabilities in array variable vProcess_Cancel_NoShow_Percent, it is rebooked and a counter for cancellation (a<process>Cancel for tests and a<process>_VisitCancel for provider visits) or failure to attend (a<process>NoShow) is incremented.

Other entity types include an entity to represent patient-related work occurs outside of a patient visit (CPAP ProfConsult), entities to search and remove unscheduled patients for scheduling (<process> Scheduler), an entity to update the next available scheduling day for each process (Variable Updater), an entity to update the next available provider day for a new patient (NextNewAdjuster), an entity to transiently change future physician capacity for on-call or other duties (ProvSchedMod), and an initialization entity (SpecialInit Entity) that generates visit histories and visit types for CPAP and PSG visits. All entities besides patient entities exist for model operation only and there are no statistics collected on them.

The arrival pattern and case mix of patient entities can be changed to reflect stationary and non-stationary (e.g. Cyclical) arrival of referrals. Current data limitations preclude the inclusion of both comorbid illnesses and sleep diagnoses as patient attributes. The model can be modified to incorporate this data when it becomes available.

Resources

The human resources that are modeled include clinicians and CPAP respiratory therapists (RT). Each of these have variable capacities and number of working hours depending on the day of the week (Schedule modules are used for CPAP_ClinicRT and CPAP_PhoneRT; the variable <clinician_type>_Hours_CapacityByDayOfWeek indexed by CalDayOfWeek is used to define clinician availability). Physicians may not have clinics scheduled every week due to on-call responsibilities and administrative commitments; these variations in resource capacity are represented in the model as

transient capacity changes (controlled by an entity to change physician schedules based on an array variable vProbCancelClinic). Clinicians are categorized by expertise (RespMD, GenIntMD, OSAonlyMD, NeuroMD, Psych). Although there may be more than one practitioner within a particular clinician type at the SC, practitioners within a clinician type are represented as a single resource with variable capacity, and are not represented as individual providers (e.g. 6 respirologists who provide 7 clinics per week in total are represented as a RespMD resource with variable daily capacity to total 7 clinics/week). CPAP RTs also provide different functions within the CPAP process (clinic and phone encounters) and spend approximately 12 hours daily completing paperwork related to patient care (modeled using the entity named CPAP ProfConsult). Clerical staff are assumed infinite and are ignored in this model.

Other resources include PSG beds and SSAT machines. There are 4 PSG beds available on 5 nights per week (Sunday to Thursday). There are 9 SSAT machines available on 5 nights per week (Monday to Friday).

For the PSG process, resource capacity is determined by the number of available testing slots (vPSGCapacityByDayOfWeek indexed by CalDayOfWeek). PSG technologist capacity is not modeled explicitly. Some patients have more complex resource needs for their PSG (aPSGTcCO2). There is a limit on the number of these tests that can be performed each night; this limit varies with the number of PSG technologists available on a given night (vTcCO2SlotsByDayOfWeek indexed by CalDayOfWeek). Some patients require a daytime test called a Mean Sleep Latency Test (aPSGMSLT), which are

performed in the PSG beds on Monday, Tuesday and Thursday. Up to 2 MSLT tests are scheduled on Monday and Tuesday, and up to 1 test on Thursday (vMSLTSlotsByDayOfWeek indexed by CalDayOfWeek).

Resource capacities for tests are parameterized in the model. Both the capacity of a given resource or the distribution of its capacity during the week can be modified to test the effects of alternative resource configurations on model performance. Furthermore, if a longer run with stepwise changes in capacity (e.g. One 0.5 full-time equivalent CPAP RT added every 2 years) is desired, the model can be adapted accordingly.

Scheduling

Scheduling of patients for visits involves a virtual 'scheduler' entity (<process> Scheduler) that selects patients (using Search/Remove modules) from the queue of patients waiting to be scheduled (Await<process>Sched.queue). This selection is based on process-specific queueing policies (a<process>QueuePriority). Patients selected to be scheduled pass through a scheduling algorithm (VBA) that puts them into the schedule for the particular process. Once patients are scheduled, they undergo a waiting period for their appointment (delay of a<process>SchedDate-TNOW days). Process-specific scheduling is described below.

The scheduling of appointments for the SSAT and PSG processes involves the allocation of a patient to one slot for an entire night. In the current system, this translates to 4 slots for PSG and 9 slots for SSAT on the nights that these resources are available. Patients are put into the schedule (array variables v<process>Sched) as slots become available,

with a finite scheduling horizon. When the next available day with an open slot (vNextAvail<process>Day) is at the scheduling horizon, no further patients are scheduled until the next available day is again within the horizon. Patients wait in the scheduling queue (Await<process>Sched.queue) until the above scheduling rules are satisfied. Queue policies incorporate the date the test was requested and urgency (a<process>QueuePriority).

There are specific rules that govern whether a test can be scheduled. Specifically, there is a limit to the number of complex PSGs (vTcCO2SlotsByDayOfWeek indexed by CalDayOfWeek) that can be scheduled on any night or MSLTs (vMSLTSlotsByDayOfWeek indexed by CalDayOfWeek) that can be scheduled on any day.

Sleep clinician and CPAP visits require one provider per visit and are of variable length depending on the type of visit (a<provider>_Num15minslotsNeeded for all providers except the respirologist, and vRespMD_New15MinSlots_Weekly or vRespMD_FU15MinSlots_Weekly for the respirologist). As a result, the number of appointments for a provider on a given day varies depending on the case mix. Additionally, some physicians have reserved slots in each clinic, that can be used to schedule any patient one week before the appointment if no patients for whom the slot is reserved are available (applies to GenIntMD for new, and to RespMD for new and urgent patients). All appointment lengths are multiples of 15 minutes. Patients are slotted into a schedule in a similar manner as for tests (variable arrays may have different numbers of

cells filled depending on the number and duration of appointments). The scheduling horizon is finite for clinician appointments and infinite for CPAP appointments. Because appointments are of different lengths, the VBA algorithm searches for appointments from the current day forward rather than using an indicator of the next available appointment day (as is done for the scheduling of tests). Queues are based on the date the appointment was requested (a<process>ReqDate) for follow-up patients, and on both appointment request date and urgency (aUrgency) for new patients.

When an appointment is scheduled, changes are made to patient characteristics as described above. The patient's unique identifying number (aEntityNumber) is entered into the corresponding slot in the process schedule. For PSG appointments, the number of complex slots scheduled for that day is modified (vNumberTcCO2Today). Similarly, the number of 15 minute slots available for provider appointments (v<process>NumberSlotsUsedToday) is updated depending on how many are used by the scheduled patient. For reserved slots, a counter records the number of new or urgent patients (for whom the slots have been reserved) that have been scheduled on that day (v<provider>NumberUrgentToday, v<provider>NumNewToday).

There is a defined probability that a patient will cancel or miss a scheduled appointment (array variable vProcess_Cancel_NoShow_Percent). Patients who cancel or do not attend a scheduled appointment and have not reached the maximum number of cancellations/no-shows (stored in a<process>Cancel or a<process>NoShow) are placed back in the scheduling queue using the original requisition date (a<process>ReqDate). In

the case of a cancellation, the slot for the cancelled appointment is cleared and if applicable the indicator of the next available appointment day (vNextAvail<process>Day) is updated to the earliest day with an open slot.

Follow-up visits and tests are common for patients with sleep disorders. Patients that are scheduled for their first visit or first test can be scheduled immediately, whereas those who are undergoing repeat testing or a follow-up provider visit will have an 'obligatory delay' before being scheduled. This delay (aDesiredDelaytoVisit) is based on the actual follow-up interval from the input data. This interval is rounded down to the nearest of 1, 2, 3, 6, or 12 months, which are the usual follow-up intervals for patients. The one exception is the second physician visit without an intervening test; since treatment initiation is assumed to occur at this visit, a 6-week interval is used. When patients enter the scheduling algorithm, the VBA algorithm searches for appointment slots beginning from the desired appointment date. Provided that the desired appointment date is within the scheduling horizon and a slot is available, the patient will be scheduled for a visit.

Scheduling algorithms are based on modifiable variables wherever possible, to allow for flexibility in scheduling rules for future simulation experiments.

Pathways

There are many clinical pathways that a patient can take depending on diagnosis, physician assignment and diagnostic test results. These may include one or more visits to any number of the processes described above.

Visit data for patients in the dataset described above is read into the model from an Excel spreadsheet of patient data. This spreadsheet lists the visit order for the path of each patient (path defined by aPathIndex). For new patients, a patient category (aProvType) corresponds to a list of physician groups (aMDGroup) to whom the patient could be assigned. Within the input dataset, a physician group is assigned based on the physician seen by the actual patient in the dataset. If a patient arrives through the R&T process, the physician group attribute (aMDGroup) is changed within the model to the next available physician group on that list (vNextAvailMD_<patient category>), and all subsequent physician visits are to the same physician. Once an entity passes through a process, the model increments the visit number (aVisitNumber) for that entity. The visit number is used to direct the entity to the next process in its clinical pathway (vVisitType(aPathIndex,aVisitNumber)). When a patient has passed through all the visits in the visit trajectory for that patient in the dataset (aTotalNumVisits), the patient is discharged. The visit type for a CPAP clinic visit or PSG are also read into the model using a similar method.

Although the clinical pathways in the current model are based on actual patient visit data, the routing of patients can be altered in future studies by using predetermined clinical pathways (using Sequence modules). Such modifications will allow testing of optimal clinical pathways for patients with different characteristics.

Outcome Collection

The primary and secondary performance measures are collected during the first and last months of the simulation (into sets indexed by aOutcomeTime, which has an integer value for both the first month (TNOW-vWarmup<=30) and last month (TFIN-TNOW<=30)). The primary outcome is also recorded for patients with different urgency ratings (aPrimUrg, aUrgency) and who have sleep-disordered breathing (aSDB). Secondary outcomes are also reported for subgroups, including patients with different urgency ratings and patients for whom PSG was requested urgently (aPSGUrgency==1). Adherence to Canadian guidelines for initial assessment of patients with suspected sleep-disordered breathing is also reported for the 1st and last months. This measure is captured by counting the number of patients meeting guidelines and dividing by the total number of patients with sleep-disordered breathing or high-risk sleep-disordered breathing (aSDB, aHighRiskCTS). Assessment in this context can be provided by any of the clinical providers in the model (aProvider_VisitNumber==1).

Perturbations

The model was modified to demonstrate the value of existing aspects of the system and to explore possible system improvements. Each perturbation is coded in a separate model file. Specific changes include:

- Removal of triage system (NoTriage) - all new patients passing through R&T are scheduled on a first-come, first-served basis for all processes except PSG (which has a separate prioritization policy). Patients thus enter the system and are

directed to further testing and the appropriate provider(s) without prioritization by urgency rating. Scheduling and reserved slots are no longer affected by urgency. Urgency is retained to demonstrate the effect on urgency subgroups (aUrgency, aPrimUrg). There is no questionnaire process to prevent inadvertent prioritization of patients who are of highest urgency simply because a questionnaire was not sent to them. Comparisons are specifically done for 'primary urgent' patients, but other urgency categories are also recorded for future analyses.

- Removal of CPAP process (NoCPAP) - all patients are assessed by the clinician group which they saw on the visit just before the CPAP visit by changing the visits in the input dataset. If no such visit exists, then the visit is represented by the clinician group that was assigned to the patient or the visit is removed if the patient was a non-sleep centre patient (CPAP visit type "ACP New"). Naturally, the first CPAP clinic visit is no longer applicable as an outcome visit. Professional Consult work for CPAP RTs will be retained in the model, but is not used in the model outcomes.
- Addition of MD capacity (AddMD) - the capacity of the physician group with the longest average queue length at the end of simulation is increased to allow for one extra half-day clinic per week. The base case simulation revealed that the RespMD physician group had the longest queue. Thus, a RespMD clinic is added on Tuesday, with 30 minutes allotted for new and follow-up patients and 2 reserved slots for new patients. Since a CPAP RT is already available for drop-in

visits at that time, no changes were made to the CPAP RT capacity or the number of available CPAP slots for scheduling.

- Addition of CPAP RT capacity (AddRT) - the capacity is increased by 0.5FTE (18.125 hours per week). This capacity is added to the CPAP Clinic RT resource as per discussions with the CPAP clinic manager. Clinic RT capacity is increased on Monday (3.625 hrs), Wednesday and Friday (7.25 hours each). The number of scheduled slots available (vCPAP_ClinicSchedSlots_ByDayOfWeek indexed by CalDayOfWeek) on those days is increased by 12 on Monday and 24 on Wednesday and Friday.
- Addition of MD and CPAP RT capacity (AddMD_RT) - the capacity of both resources is changed as outlined in the AddMD and AddRT scenarios, above.

Increased Demand Case

The arrival rate was increased using population growth estimates for the City of Calgary. The mean for the Poisson distribution describing the weekly arrivals was adjusted to reflect this increase (5.06%).

Areas of Flexibility of the Model

As discussed above, the model is flexible in many areas and could be used to test a number of alternative scenarios not mentioned above. Other examples include:

- Changes to triage criteria - by adding the specific criteria (rather than urgency status alone), the effects of changing the criteria on model performance could be tested.

- Diagnosis or comorbidity based queueing policies or clinical pathways
- Limiting utilization of CPAP clinic by individual patients - setting a maximum number of visits could be used to relieve the congestion at this process, especially if there is evidence that the incremental benefit of further visits after a certain number is diminished.

Running Commentary on DES Model

The following bullet points are additional comments on nuances of the model

- Used aDesiredDelaytoVisit instead of delay module because could not incorporate a v<process>NextAvailDay for MD processes (multiple slot values required)
    - Delay is max(0,aDesiredDelaytoVisit-vMDSchedHorizon) for MD visits to ensure that entity is released to scheduling queue at earliest possible date that slot could be available (for CPAP - no scheduling horizon, so no such delay)
    - In VBA - start looking at later of vNextAvail<process>Day or aLastVisitDate+aDesiredDelaytoVisit
- Record number for Read module is anint(unif(0.5,150.4999)) to ensure 150.5 (rounds to 151) does not occur
- Change MD/Psych schedule with fixed probability in future (always look at 91st day). Also adjust CPAP clinic schedule accordingly (increase CPAP appointment slots if MD clinic slots are decreased)

    - NeuroMD (2.5 hours) and GenIntMD (3.5 hours) are not 3 hour clinics - used modified expressions to return 0: max(0,vNeuroMD_Hours -3) and aint(0,vGenIntMD_Hours -3)
- If use next available appointment based on patient category, cannot combine MD submodels by patient category - there are MD group specific behaviours that need to be preserved - will use next available approach, but will still separate MD groups
    - If next available new day is same for MD groups, randomly select MD group
    - Will assign MD group to all patients that day, even if next available MD group should change by assigning previous patients that day
    - Included urgent slots in available slots - artificially increases delays for all but NoTriage scenario (RespMD always looks to have available slots), but attempted to preserve access for urgent patients
- Reserved slots - for RespMD and GenIntMD only - have reserved new and urgent slots, but no reserved f/u slots (since F/U patients are higher priority in queue, they will have first access to non-new slots)
    - For Psych, have reserved follow-up slots in similar manner

Appendix F: Model Components for Foothills Sleep Centre DES Model

General	Location	Name	Purpose	Dimensions/ Statistic Type	Key/Initial Values
Entities		Patient	Patient entities		
		SpecialInit Entity	To initialize visit array variables from Read module		
		ProvSchedMod	To initialize and change of clinic schedules in future		
		Variable Updater	To update NextAvail<process>Day to current day +1 if not >current day; and to update NextAvailNewDay for each provider		
		NextNewAdjuster	To adjust v<Mdtype>MD_NextAvailNewDay		
Attributes	Referral	aEntityNumber	Entity ID		
		aArrTime	Time of arrival to system		
		aVisitNumber	Counter of number of visits		
		aNew	Indicator of new patient status - until first provider visit		
		aCTSHighRisk	Indicator of high risk by CTS criteria		aOccRisk=1 OR aFirstSSATRDI>30 OR aFirstPSGAHI>30
	Read/Write	aPathIndex	Identifies visit path through model		
		aTotalNumVisits	Total Number of visits - to help define clinical pathway and discharge		
		aTimeInSystem	Time from first to last appointment in dataset - not used in current analysis		
		aRefTriage	Indicator that patient was referred through referral/triage process		
		aUrgency	Urgency through referral and triage process		1=urgent, 2=semi-urgent, 3=normal

		aPrimUrg	Indicator of 'primary urgent' status		
		aProvType	Provider type based on likely diagnosis from referral/triage process		1=OSA, 2=insomnia, 3=intrinsic sleep disorder, 4=respiratory disease, 5=neurologic disease, 6=chronic fatigue syndrome
		aQuestionnaireDelay	Time between receipt of referral and questionnaire date		
		aOccRisk	Indicator of safety critical occupation		
		aEpworth	Epworth Sleepiness Scale score from patient chart		
		aSSATdone	Indicator of whether patient has had SSAT before referral		
		aPSGUrgency	Urgency type for first PSG		1=urgent, 2=normal
		aFirstPSGAHI	Sleep-disordered breathing severity from first PSG		
		aFirstSSATRDI	Sleep-disordered breathing severity from first SSAT		
		aMeanSat	Mean oxygen saturation from first SSAT - not used in current model		
		aPercentBelow90	Percentage of time oxygen saturation is < 90% on first SSAT - not used in current analysis		
		aMDGroup	MD group to which patient is assigned (may change based on next available appointment)		
	Post Visit	aLastVisitDate	Date of last visit to calculate delay to next visit if applicable		
		aProvider_VisitNumber	Counter of non-test visits		
	Outcome	aOutcomeDone	Indicates that outcome visit has occurred (Treatment initiation)		

		aOutcomeTime	Identifies patients reaching outcomes in 1st and last month of simulation (after warmup)		
		aUrgency_OutcomeTime	Composite of urgency and outcome time for analysis of outcomes by both simultaneously		
	Other	aProviderGroup	For ProvSchedMod to index into vProbCancelClinic		
		aDayNumber	To initialize clinic capacity variable		
		aSchedChange	Indicates that capacity on day to change provider schedule is > 0		
Variables		vWIP	Number of patient entities in system		
		vVisitType	Array variable to identify next visit in sequence	150 x 15	
		vCPAPVisitType	Array to select CPAP visit type based on aPathIndex, aCPAP_VisitNumber	150 x 7	
		vPSGVisitType	Array to select PSG type based on aPathIndex, aPSGNumber	150 x 4	
		vVisitDelay	Array variable to identify desired delay after outcome visits	150 x 15	
		vProbCancelClinic	Array to define probability of cancelled clinic (indexed into aProviderGroup)	8 x 1	
		vDummySpecialInit	To initialize visit array variables		
		vNextAvailMD_1	For patient category 1, identifies MD with earliest available slot for a new patient		
		vNextAvailMD_2	For patient category 2, identifies MD with earliest available slot for a new patient		
		vNextAvailMD_3	For patient category 3, identifies MD with earliest available slot for a new patient		
		vNextAvailMD_6	For patient category 6, identifies MD with earliest available slot for a new patient		

		vProcess_Cancel_NoShow_Percent	Probability of cancellation/no-show	8 x 2	
		vWarmup	Warmup period		2000
		vMaxRunLength	Maximum possible length of a run (to define dimensions of array variable)		4000
		vActualRunLength	Actual run length for simulation		3095
Expressions		eCurrentDay	Truncate TNOW to current day		
		eCurrentTime	Expression representing TNOW (for VBA)		
Sets		Station Set	Identifies each station for patient visits		
		s1stMD_PrimUrg_OutcomeTime	For 1st MD Visit		
		sNumHighRisk_ByOutcomeTime	For Canadian Wait Time guidelines		1=no SDB, 2=SDB
		sNumHighRiskSDBNotMeetingCTS_ByOutcomeTime	For Canadian Wait Time guidelines		
		sNumSDB_ByOutcomeTime	For Canadian Wait Time guidelines		
		sNumSDBNotMeetingCTS_ByOutcomeTime	For Canadian Wait Time guidelines		
		sTime1stMDVisitByOutcomeTime	For 1st MD Visit		
		sTime1stMDVisitByUrgency	Not used in current analysis		
		sTime1stMDVisitByUrgency_OutcomeTime	Not used in current analysis		
		sTime1stProvVisit_ByOutcomeTime	Not used in current analysis		
		sTime1stPSGByOutcomeTime	For 1st PSG		
		sTime1stPSGByPSGUrgency	Not used in current analysis		
		sTime1stPSGByPSGUrgency_OutcomeTime	For 1st PSG		
		sTime1stPSGByTriageUrgency	Not used in current analysis		
		sTime1stPSGByUrgency_OutcomeTime	Not used in current analysis		
		sTtreat_PrimUrg_ByOutcomeTime	For Time to treatment initiation		
		sTtreatByOutcomeTime	For Time to treatment initiation		
		sTtreatByUrgency	Not used in current analysis		
		sTtreatByUrgency_OutcomeTime	Not used in current analysis		
		sTtreatforSDB_OutcomeTime	For Time to treatment initiation		
Statistics		Ttreat_LastMonth	Time to treatment initiation for patients reaching outcome in last month - for verification	Output	
		Ttreat_Trend	Not used in current analysis	Output	

		Ttreat_Trend_PercentChange	Percent change in time to treatment initiation from 1st to last month - for verification	Output	
		Number of Patients in System	Not used in current analysis	Output	
Random Number Streams		14	RNS for Poisson distribution of arrivals		

SSAT	Location	Name	Purpose	Dimensions/ Statistic Type	Initial values
Entities	SSAT Scheduler	SSAT Scheduler	Entity to schedule SSATs for patients in queue		
Attributes	SSATRequisition Attributes	aSSATReqDate	Date that SSAT is requested		
		aSSATSchedDate	Date of scheduled SSAT		
		aSSATNumber	Counter of number of SSATs that patient has undergone		
		aSSATQueuePriority	For Infinite Hold ordering within queue		
		aDesiredDelaytoVisit	Desired Interval before next visit		
	SSAT Cancellation Attributes	aSSATCancelCount	Counter of number of cancelled SSATs		
	SSAT NoShow Attributes	aSSATNoShow	Counter of number of missed SSATs		
	Post SSAT Attributes	aSDB	Indicator of sleep-disordered breathing based on AHI, RDI or CPAP visit	y	
	SSAT Scheduler Attributes	aNumberSSATScheduled	Counter of number of SSAT schedule attempts (to minimize scheduling loops by scheduler)		
Variables	SSAT Scheduling	vSSATSched	Schedule for SSAT (array variable) - includes aEntityNumber for scheduled entities	4000x9	
		vNextAvailSSATDay	Day that next available SSAT slot is available to book		1
		vRowsSSATSchedArray	Number of rows in SSAT Schedule over simulation		vMaxRunLength

		vColsSSATSchedArray	Number of columns in SSAT Schedule over simulation		9
		vSSATCapacityByDayOfWeek	SSAT slots by day of week - indexed by CalDayOfWeek	7 x 1	
		vSSATSchedHorizon	Planning horizon for SSAT scheduling (depends on new vs. follow-up test)	1+2	
Expressions		eSSATSchedHorizon	Evaluates to difference between next available SSAT day and current day - for verification		
Queues		AwaitSSATSched.queue	Queue for patients awaiting SSAT scheduling (until removed by Search/Remove modules)		

PSG	**Location**	**Name**	**Purpose**	**Dimensions/ Statistic Type**	**Initial values**
Entities	PSG Scheduler	PSG Scheduler	Entity to schedule PSGs for patients in queue		
Attributes	PSGRequisition Attributes	aPSGReqDate	Date that PSG is requested		
		aPSGTcCO2	Indicator for TcCO2 - based on PSG type from R/W	y	
		aPSGMSLT	Indicator for MSLT - based on PSG type from R/W	y	
		aPSGQueuePriority	To order PSG reqs in queue		
		aPSGNumber	Counter of number of PSGs that patient has undergone		
		aPSGSchedDate	Date of scheduled PSG		
		aDesiredDelaytoVisit	Desired interval before next visit		
	PSG Cancellation Attributes	aPSGCancel	Counter of number of cancelled PSGs		
	PSG No Show Attributes	aPSGNoShow	Counter of number of no-show PSGs		
	Post PSG Attributes	aSDB	Indicator of sleep-disordered breathing based on AHI, RDI or CPAP visit	y	

	PSG Scheduler Attributes	aNumberSchedforPSG	Counter of number of PSG schedule attempts (to minimize scheduling loops for scheduler)		
Variables	PSG Scheduling	vPSGSched	Schedule for PSG (array variable) - includes aEntityNumber for scheduled entities	4000x4	
		vNextAvailPSGDay	Day that next available PSG slot is available to book		1
		vRowsPSGSchedArray	Number of rows in PSG Schedule over simulation		vMaxRunLength
		vColsPSGSchedArray	Number of columns in PSG Schedule over simulation		4
		vNumberTcCO2Today	Counter for number of TcCO2 tests requested on a given day	4000 x 1	
		vTcCO2SlotsByDayOfWeek	TcCO2 slots by day of week - indexed by CalDayOfWeek	7 x 1	
		vMSLTSlotsByDayOfWeek	MSLT slots by day of week - indexed by CalDayOfWeek	7 x 1	
		vNumberMSLTToday	Counter for number of MSLT tests requested on a given day	4000 x 1	
		vPSGCapacityByDayOfWeek	PSG slots by day of week - indexed by CalDayOfWeek	7 x 1	
		vPSGSchedHorizon	Defines planning horizon for PSG Scheduling		30
Expressions		ePSGSchedHorizon	Evaluates difference between next available PSG day and current day - for verification		
Queues		AwaitPSGSched.queue	Queue for patients awaiting PSG scheduling (until removed by Search/Remove modules)		

CPAP	**Location**	**Name**	**Purpose**	**Dimensions/ Statistic Type**	**Initial values**
Entities		CPAP Scheduler	Entity to schedule CPAP visits for patients in queue		

		CPAP ProfConsult	Entity to load CPAP RTs with 4 hours of paperwork each day		
Attributes	CPAP Scheduling Attributes	aCPAPReqDate	Date that CPAP visit is requested		
		aCPAP_VisitNumber	Number of CPAP visits that patient has had		
		aCPAP_VisitSchedDate	Date of scheduled CPAP visit		
		aOKforPhoneCPAP	Indicator of phone visit suitability	y	
		aDesiredDelaytoVisit	Desired interval before next visit		
		aCPAP_Num15minslotsNeeded	Time needed by visit type - indexed into vCPAP_Num15MinSlotsNeeded		
	CPAP Cancellation Attributes	aCPAPCancelCount	Counter of number of cancelled CPAP appointments		
	CPAP No-show Attributes	aCPAPNoShow	Counter of number of no-show CPAP visits		
	Post CPAP Visit Attributes	aLTFU	Indicator of LTFU status (based on visit type from R/W)	y	
		aSDB	Indicator of sleep-disordered breathing based on aFirstPSGAHI, aFirstSSATRDI or CPAP visit	y	
	CPAP Scheduler Attributes	aNumberSchedforCPAP	Counter of number of CPAP schedule attempts (to minimize scheduling loops for scheduler)		
Variables		vCPAPSched	Schedule for CPAP (array variable) - includes aEntityNumber for scheduled entities		
		vRowsCPAPSchedArray	Number of rows in CPAP Schedule over simulation		vMaxRunLength
		vColsCPAPSchedArray	Number of slots in CPAP schedule		50
		vCPAP_ClinicSchedSlots_ByDayOfWeek	Number of 15 minute slots available for scheduling each weekday	7 x 1	
		vCPAPNumberSlotsUsedToday	Number of 15 minute slots used on given day	4000 x 1	
		vNextAvailCPAPDay	To advance scheduling loop in VBA		1
		vCPAP_Num15MinSlotsNeeded	Array for appointment lengths	8 x 1	

		vCPAP_NumSchedSlotsToday	Number of available slots for scheduled appointments - to change as MD schedules change	4000 x 1	
Resources		CPAP_ClinicRT	Performs clinic visits, 'drop-in' visits, Professional Consult Work		
		CPAP_PhoneRT	Performs phone visits and Professional Consult Work		
Queues		AwaitCPAPSched.queue	Queue for patients awaiting CPAP scheduling (until removed by Search/Remove modules)		
		CPAP Process.queue			
		CPAP Professional Consult Work.queue			
		CPAP Phone Visit.queue			
Schedules		CPAP_ClinicRT_Schedule			
		CPAP_PhoneRT_Schedule			
Sets		CPAP_RT Set	For 'Professional Consult' work - selects resource to do work from set		
Statistics		CPAP_RT Utilization	Combines Clinic and Phone RTs - for verification/validation	Output	

RespMD	Group/Module	Name	Purpose	Dimensions/ Statistic Type	Initial values
Entities		RespMD Scheduler	Entity to schedule RespMD visits for patients in queue		
Attributes	MD Scheduling Attributes	aRespMDReqDate	Date that RespMD visit is requested		
		aRespMD_VisitSchedDate	Date of scheduled RespMD visit		
		aMD_VisitNumber	Count of number of visits to any MD		
		aRespMD_QueuePriority	Defines queue priority for RespMD scheduling queue		
		aDesiredDelaytoVisit	Desired interval before next visit		
	MD Cancellation Attributes	aMD_VisitCancel	Counter of number of cancelled MD appointments		
	MD No-show Attributes	aMDNoShow	Counter of number of no-show MD visits		

-	Scheduling Attributes	aNumberSchedforRespMD	Counter of number of RespMD schedule attempts (to minimize scheduling loops by scheduler)		
Variables	MD Scheduling	vRespMDSched	Schedule for RespMD (array variable) - includes aEntityNumber for scheduled entities		
		vRowsRespMDSchedArray	Number of rows in RespMD Schedule over simulation		vMaxRunLength
		vColsRespMDSchedArray	Number of slots in RespMD schedule		50
		vRespMD_Hours_CapacityByDayOfWeek	RespMD capacity by day of week indexed by CalDayOfWeek	7 x 1	
		vRespMDNumberSlotsUsedToday	Number of 15 minute slots used	4000 x 1	
		vNextAvailRespMDDay	To advance scheduling loop in VBA		1
		vRespMDNumNewToday	Number of new patients scheduled today	4000 x 1	
		vRespMDNumNewPerClinic_ByDayOfWeek	Number of new RespMD patients required per clinic indexed by CalDayOfWeek	7 x 1	
		vRespMD_NumUrgentToday	Daily counter of urgent RespMD patients	4000 x 1	
		vRespMDNumUrgentPerClinic_ByDayOfWeek	Number of urgent RespMD patients required per clinic indexed by CalDayOfWeek	7 x 1	
		vRespMD_New15MinSlots_Weekly	Number of 15 minute slots required for new patients indexed by CalDayOfWeek	7 x 1	
		vRespMD_FU15MinSlots_Weekly	Number of 15 minute slots required for follow-up patients indexed by CalDayOfWeek	7 x 1	
		vRespMD_Hours_CapacityToday	Capacity on a given day - may change with clinic cancellations, etc.	4000 x 1	
		vRespMD_NextAvailNewDay	Next day with enough slots to accommodate a new patient		
		vMDSchedHorizon	Planning horizon for MD appointments		90
		vProbCancelClinic	Probability that provider will cancel clinic 91 days in future	8 x 1	

Queues		AwaitRespMD_VisitSched.queue	Queue for patients awaiting RespMD scheduling (until removed by Search/Remove modules)		

NeuroMD	Group/Module	Name	Purpose	Dimensions/ Statistic Type	Initial values
Entities		NeuroMD Scheduler	Entity to schedule NeuroMD visits for patients in queue		
Attributes	MD Scheduling Attributes	aNeuroMDReqDate	Date that NeuroMD visit is requested		
		aNeuroMD_VisitSchedDate	Date of scheduled NeuroMD visit		
		aMD_VisitNumber	Count of number of visits to any MD		
		aNeuroMD_QueuePriority	Defines queue priority for NeuroMD scheduling queue		
		aNeuroMD_Num15MinSlotsNeeded	Number of slots needed for NeuroMD visit		
		aDesiredDelaytoVisit	Desired interval before next visit		
	MD Cancellation Attributes	aMD_VisitCancel	Counter of number of cancelled MD appointments		
	MD No-show Attributes	aMDNoShow	Counter of number of no-show MD visits		
-	Scheduling Attributes	aNumberSchedforNeuroMD	Counter of number of NeuroMD schedule attempts (to minimize scheduling loops by scheduler)		
Variables	MD Scheduling	vNeuroMDSched	Schedule for NeuroMD (array variable) - includes aEntityNumber for scheduled entities		
		vRowsNeuroMDSchedArray	Number of rows in NeuroMD Schedule over simulation		vMaxRunLength
		vColsNeuroMDSchedArray	Number of slots in NeuroMD schedule		50
		vNeuroMD_Hours_CapacityByDayOfWeek	NeuroMD capacity by day of week indexed by CalDayOfWeek	7 x 1	
		vNeuroMDNumberSlotsUsedToday	Number of 15 minute slots used	4000 x 1	
		vNextAvailNeuroMDDay	To advance scheduling loop in VBA		1

		vNeuroMD_Hours_CapacityToday	Capacity on a given day - may change with clinic cancellations, etc.	4000 x 1	
		vNeuroMD_NumSlots_NewFU	Number of 15 minute slots required for new and follow-up patients	1 x 2	
		vNeuroMD_NextAvailNewDay	Next day with enough slots to accommodate a new patient		
		vMDSchedHorizon	Planning horizon for MD appointments		90
		vProbCancelClinic	Probability that provider will cancel clinic 91 days in future	8 x 1	
Queues		AwaitNeuroMD_VisitSched.queue	Queue for patients awaiting NeuroMD scheduling (until removed by Search/Remove modules)		

OSAonlyMD	**Group/Module**	**Name**	**Purpose**	**Dimensions/ Statistic Type**	**Initial values**
Entities		OSAonlyMD Scheduler	Entity to schedule OSAonlyMD visits for patients in queue		
Attributes	MD Scheduling Attributes	aOSAonlyMDReqDate	Date that OSAonlyMD visit is requested		
		aOSAonlyMD_VisitSchedDate	Date of scheduled OSAonlyMD visit		
		aMD_VisitNumber	Count of number of visits to any MD		
		aOSAonlyMD_QueuePriority	Defines queue priority for OSAonlyMD scheduling queue		
		aOSAonlyMD_Num15MinSlotsNeeded	Number of slots needed for OSAonlyMD visit		
		aDesiredDelaytoVisit	Desired interval before next visit		
	MD Cancellation Attributes	aMD_VisitCancel	Counter of number of cancelled MD appointments		
	MD No-show Attributes	aMDNoShow	Counter of number of no-show MD visits		
-	Scheduling Attributes	aNumberSchedforOSAonlyMD	Counter of number of OSAonlyMD schedule attempts (to minimize scheduling loops for scheduler)		

Variables	MD Scheduling	vOSAonlyMDSched	Schedule for OSAonlyMD (array variable) - includes aEntityNumber for scheduled entities		
		vRowsOSAonlyMDSchedArray	Number of rows in OSAonlyMD Schedule over simulation		vMaxRunLength
		vColsOSAonlyMDSchedArray	Number of slots in OSAonlyMD schedule		50
		vOSAonlyMD_Hours_CapacityByDayOfWeek	OSAonlyMD capacity by day of week indexed by CalDayOfWeek	7 x 1	
		vOSAonlyMDNumberSlotsUsedToday	Number of 15 minute slots used	4000 x 1	
		vNextAvailOSAonlyMDDay	To advance scheduling loop in VBA		1
		vOSAonlyMD_Hours_CapacityToday	Capacity on a given day - may change with clinic cancellations, etc.	4000 x 1	
		vOSAonlyMD_NumSlots_NewFU	Number of 15 minute slots required for new and follow-up patients	1 x 2	
		vOSAonlyMD_NextAvailNewDay	Next day with enough slots to accommodate a new patient		
		vMDSchedHorizon	Planning horizon for MD appointments		90
		vProbCancelClinic	Probability that provider will cancel clinic 91 days in future	8 x 1	
Queues		AwaitOSAonlyMD_VisitSched.queue	Queue for patients awaiting OSAonlyMD scheduling (until removed by Search/Remove modules)		

GenIntMD	**Group/Module**	**Name**	**Purpose**	**Dimensions/ Statistic Type**	**Initial values**
Entities		GenIntMD Scheduler	Entity to schedule GenIntMD visits for patients in queue		
Attributes	MD Scheduling Attributes	aGenIntMDReqDate	Date that GenIntMD visit is requested		
		aGenIntMD_VisitSchedDate	Date of scheduled GenIntMD visit		
		aMD_VisitNumber	Count of number of visits to any MD		

		aGenIntMD_QueuePriority	Defines queue priority for GenIntMD scheduling queue		
		aGenIntMD_Num15MinSlotsNeeded	Number of slots needed for GenIntMD visit		
		aDesiredDelaytoVisit	Desired interval before next visit		
	MD Cancellation Attributes	aMD_VisitCancel	Counter of number of cancelled MD appointments		
	MD No-show Attributes	aMDNoShow	Counter of number of no-show MD visits		
-	Scheduling Attributes	aNumberSchedforGenIntMD	Counter of number of GenIntMD schedule attempts (to minimize scheduling loops by scheduler)		
Variables	MD Scheduling	vGenIntMDSched	Schedule for GenIntMD (array variable) - includes aEntityNumber for scheduled entities		
		vRowsGenIntMDSchedArray	Number of rows in GenIntMD Schedule over simulation		vMaxRunLength
		vColsGenIntMDSchedArray	Number of slots in GenIntMD schedule		50
		vGenIntMD_Hours_CapacityByDayOfWeek	GenIntMD capacity by day of week indexed by CalDayOfWeek	7 x 1	
		vGenIntMDNumberSlotsUsedToday	Number of 15 minute slots used	4000 x 1	
		vNextAvailGenIntMDDay	To advance scheduling loop in VBA		1
		vGenIntMD_Hours_CapacityToday	Capacity on a given day - may change with clinic cancellations, etc.	4000 x 1	
		vGenIntMD_NumSlots_NewFU	Number of 15 minute slots required for new and follow-up patients	1 x 2	
		vGenIntMD_NumNewToday	Counter of new patients in clinic on a given day	4000 x 1	
		vGenIntMD_NumNewPerClinic	Required number of new patients in each clinic		4
		vGenIntMD_NextAvailNewDay	Next day with enough slots to accommodate a new patient		
		vMDSchedHorizon	Planning horizon for MD appointments		90
		vProbCancelClinic	Probability that provider will cancel clinic 91 days in future	8 x 1	

Queues		AwaitGenIntMD_VisitSched.queue	For Infinite Hold until removed by Search/Remove		

Psych	Group/Module	Name	Purpose	Dimensions/ Statistic Type	Initial values
Entities		Psych Scheduler	Entity to schedule Psych visits for patients in queue		
Attributes	Psych Scheduling Attributes	aPsychReqDate	Date that Psych visit is requested		
		aPsych_VisitNumber	Number of Psych visits that patient has had		
		aPsych_VisitSchedDate	Date of scheduled Psych visit		
		aPsych_Num15minslotsNeeded	Time needed by visit type		
		aDesiredDelaytoVisit	Desired interval before next visit		
		aPsych_QueuePriority	Defines queue priority for Psych scheduling queue		
	Psych Cancellation Attributes	aPsych_VisitCancel	Counter of number of cancelled Psych appointments		
	Psych No-show Attributes	aPsychNoShow	Counter of number of no-show Psych visits		
	Psych Scheduler Attributes	aNumberSchedforPsych	Counter of number of Psych schedule attempts (to minimize scheduling loops by scheduler)		
Variables	Psych Scheduling	vPsychSched	Schedule for Psych (array variable) - includes aEntityNumber for scheduled entities		
		vRowsPsychSchedArray	Number of rows in Psych Schedule over simulation		vMaxRunLength
		vColsPsychSchedArray	Number of slots in Psych schedule		50
		vPsych_Hours_CapacityByDayOfWeek	Psych capacity by day of week indexed by CalDayOfWeek	7 x 1	
		vPsychNumberSlotsUsedToday	Number of 15 minute slots used	4000 x 1	
		vNextAvailPsychDay	To advance scheduling loop in VBA		1
		vPsych_NumSlots_NewFU	Number of 15 minute slots for new and follow-up appointments	1 x 2	
		vPsych_Hours_CapacityToday	Capacity on a given day - may change with clinic cancellations, etc.	4000 x 1	

		vPsych_NumFUToday	Counter of follow-up patients in each clinic	4000 x 1	
		vPsych_NumFUPerClinic	Required number of follow-up patients in each clinic		2
		vMDSchedHorizon	Planning horizon for MD appointments		90
		vProbCancelClinic	Probability that provider will cancel clinic 91 days in future	8 x 1	
Queues		AwaitPsych_VisitSched.queue	For Infinite Hold until removed by Search/Remove		